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Collaboration Dynamics in Virtual Innovation Teams:

A Longitudinal Social Network Analysis

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A Longitudinal Social Network Analysis

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Epigraph and Dedication

"We are here to make a better world." – W. Edwards Deming

This dissertation is dedicated to Reuben R. McDaniel, Jr.

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by

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There is a need for practical wisdom around innovative behaviors in modern organizations, in which online collaboration supports the creation of value and knowledge. Virtual teams – a strategy for innovation used increasingly in organizations – face challenges of knowledge integration and coordination across time and space. Collaborative structures and communication patterns that distinguish thriving virtual innovation teams are not well defined. With this dissertation, we explored how collaborative structures of virtual teams change over time and considered the extent to which these dynamics may impact innovation processes and performance.

This longitudinal study of eleven virtual teams in the context of a health care system design project seeks new theoretical insights about innovation in distributed groups. Our primary data were collected from digital archives of project email correspondence over twenty-three months. We used social network analysis to observe structures and interactions in team email communication networks. We examined team centrality,

structural dynamics, and participation equality as potential drivers of virtual innovation team outcomes, also considering how distinctive innovation process phases (e.g., design, testing, implementation) during the innovation team lifespan moderated these relationships. We found partial support for the six hypotheses tested. As predicted, participation equality was positively associated with work group performance and structural dynamics was positively associated with radical innovation. Contrary to what we predicted, team centrality was positively associated with performance and innovation. We observed interesting variation in these relationships across four innovation process phases.

This research contributes to what is known about the temporality of virtual innovation teams and more generally about virtual team performance. Results from this study could inform the design and management of future virtual innovation teams and the ecosystems in which they are embedded.

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CHAPTER 1: INTRODUCTION

The purpose of this dissertation is to explore how collaborative structures of virtual teams change over time and to what extent these dynamics impact innovation processes and performance. Groundbreaking solutions to complex problems and designs for new and better systems require extended efforts of diverse individuals. Fortuitously, the internet has afforded new and extraordinary opportunities for collaboration across time and space (Benkler 2006; Colbert et al. 2016). This organizational paradigm shift towards a digitally enabled workforce brought about the primacy of virtual teams as an organizational design choice (Gilson et al. 2015; Martins et al. 2004). The purpose of this dissertation research is to gain socially relevant understanding (Flyvbjerg et al. 2012) with respect to collaboration dynamics of virtual innovation teams.

Innovation is an ensemble phenomenon. It is accomplished via networks of individuals and teams (Fjeldstad et al. 2012; King and Anderson 1990). We define virtual teams as "teams whose members use technology to varying degrees in working across locational, temporal, and relational boundaries to accomplish an interdependent task" (Martins et al. 2004, p. 808). Virtual team functioning is imperative for organizational thriving and sustained competitive advantage (Jarvenpaa and Tanriverdi 2003; Kanawattanachai and Yoo 2007). Dominant in team research is the input-process-outcome model (Hackman and Morris 1974; McGrath 1964), implying that membership, resources, and criteria with which to evaluate performance are fixed. Yet innovation teams – teams working to develop and implement new ideas – confront ever-shifting constellations of means and ends (Edmondson and Nembhard 2009). Consideration of innovation not as a discrete, individual activity but rather the dynamic social process of developing and implementing new ideas (Schumpeter 1934; Van de Ven et al. 2000) underscores the importance of timely and effective coordination in virtual innovation teams.

The co-evolution of information technology and organizational forms has changed conceptualizations of collective learning and competitive advantage (Arthur 2009; Dougherty and Dunne 2011; Kane and Alavi 2007). The twenty-first century has seen the rise of decentralized virtual organizations (Carley and Ahuja 1999) driven by informal, electronically-mediated interactions (Desanctis and Monge 1998; Monge and Contractor 2001). Virtual innovation teams gain from capabilities to self-organize around relevant goals and resources more so than traditional managerial levers (Beyerlein and Johnson 1994; McDaniel 2007; Zammuto et al. 2007). Team processes at the essence are "widespread narrative patterns emerging in local interactions" (Stacey 2010: 214). Teams with similar inputs and skills could vary greatly with respect to interpersonal relationships, and it is the latter that often differentiate team outcomes (Carmeli et al. 2009; Edmondson 2012).

Team performance is a function of group-level emergent processes more so than static characteristics of individual team members and other resources (e.g., Kane and Borgatti 2011). The proverbial 'sum as more than its parts' concept applies to teams in the sense that value becomes embedded in collective social structures (Lewis et al. 2007; Tziner and Eden 1985). Thus recognition of the gestalt and non-linear nature of team processes and structures (Curşeu 2006; Gilson et al. 2015) is important in understanding virtual innovation team effectiveness.

The science of networks offers a useful and growing collection of models and methods to help scholars and managers make sense of interconnected systems (Borgatti et al. 2009; Easley and Kleinberg 2010; Lazer et al. 2009). The network paradigm has illuminated interpersonal, intra-, and inter-organizational phenomena in both theory and practice (Borgatti and Foster 2003; Brass et al. 2004). For example, network-based theories have explained multiple facets of management information systems (Oinas-Kukkonen et al. 2010), the co-evolution of information technology and social elements in business contexts (Agarwal et al. 2008; Kane and Alavi 2008; Sykes et al. 2009), the nature of user-generated digital content (Dutton 2008), and elements of intergroup collaboration (Borgatti and Cross 2003; Cummings 2004; Jarvenpaa and Majchrzak 2008). Organizational forms (conventional and of the digital age) have been widely conceptualized as networks (e.g., Carley and Ahuja 1999). Consideration of interactions and structural dynamics with a network lens could offer an enriched view of how increasingly pervasive virtual teams evolve (Gilson et al. 2015).

1.1 Research Question

Collaboration dynamics and network models are prominent in the outpouring of recent innovation studies (Hülsheger et al. 2009; Levine and Prietula 2013; Wolfe 1994) and in the popular innovation literature (Christensen and Raynor 2013; Govindarajan and Trimble 2010; Miller and Wedell-Wedellsborg 2013). Research on team-level innovation places communication and cohesion among key drivers of success (Hülsheger et al. 2009). Yet fewer studies have examined the nature of interactions among innovators in virtual teams. Also sparse are scholarly interpretations of the temporal nature of collaboration dynamics in virtual teams (Gilson et al. 2015) and the evolutionary momentum of innovation-seeking groups (Anderson et al. 2014).

Academics as well as those who design, manage, and/or participate in modern innovation initiatives could benefit from enhanced understanding of the sequential and emergent nature of collaboration (Anderson et al. 2014). How do the collaborative structures of virtual teams change over time and to what extent do these dynamics impact innovation processes and performance?

We explored this research question with a longitudinal study of virtual innovation teams participating in a large-scale health care system re-design project. Our methodological approach was designed to consider temporality and to afford theorization about virtual innovation teams in ways that the existing proliferation of time-invariant cross-sectional studies cannot (Zaheer et al. 1999). Using social network analysis, we characterized the network centrality structures and communication patterns of eleven teams over thirty months. Field study methods and ethnographic immersion in the research context offer a nuanced view of virtual innovation teams and complement our digital observations. This research will examine how collaboration processes evolve for virtual teams, the increasingly common approach to tackling complex problems and generating innovative solutions in modern organizations.

1.2 Dissertation Guide

This introductory chapter has motivated our research question and provided background information on virtual teams, innovation teams, and a network-based paradigm for conceptualizing collaborative team structures.

Chapter 2 will delineate the current literatures on virtual teams and team innovation. We identify distinctive opportunities and challenges facing virtual innovation teams. We also provide background on the use of social network analysis (SNA) to model human interactions and study behavioral phenomena.

Chapter 3 will outline our theorization about network structures and communication dynamics with six hypotheses. We consider team centrality, structural dynamics, and participation equality as potential drivers of virtual innovation team performance and radical innovation. We also consider how these relationships might vary as a function of the innovation phase (e.g., designing, testing, implementing) in which teams are operating.

Chapter 4 will describe our research context, data sources, and methodological design choices. We tested our hypotheses by analyzing variation in the email communication networks of eleven virtual innovation teams collaborating under the auspices of a large-scale health care system design project. Data were collected from digital archives of team email correspondence and from ratings of team performance outcomes from senior leadership of the project.

Chapter 5 will describe the structure of our panel dataset. We summarize findings from diagnostic testing and implications for model selection. We specify models used to test hypotheses: linear regression with panel-corrected standard errors and random intercept mixed models. The final section of this chapter conveys estimation model results with accompanying graphics for each hypothesis tested.

We found limited support for the six hypotheses tested. As predicted, participation equality is positively associated with virtual innovation team performance and structural dynamics is positively associated with radical innovation. Contrary to what we predicted, team centrality is positively associated with performance and innovation. We observed interesting variation in these relationships across four innovation process phases.

Chapter 6 will discuss implications of our results and revisit the theoretical model described in Chapter 3. Chapter 7 will conclude the dissertation. Here we will consider limitations to the conclusions that we can draw from our results and interesting avenues for future research. Results from this study could inform design and management of future virtual innovation teams and the ecosystems in which they are embedded. Our methodology is innovative and offers a guide for longitudinal studies drawing on digital exhaust from online communication. We contribute to theories of collaboration in virtual innovation teams and more generally to understanding of virtual team performance.

CHAPTER 2: LITERATURE REVIEW

This chapter will outline the theoretical domains of virtual teams and team innovation. We identify distinctive opportunities and challenges facing virtual innovation teams and consider temporality of collaborative innovation over time and innovation process phases. Also discussed is scholarly use of social network analysis to observe behavioral phenomena and to model interaction structures.

2.1 Virtual Teams

Teams, established groups of people working in pursuit of shared goals, produce something useful for themselves and for their organizations (Argote and McGrath 1993; Mathieu et al. 2008). A virtual team is one in which members collaborate across geographical and organizational boundaries with interactions mediated to some extent by technology (Martins et al. 2004). Digitally-driven collaboration promises new levels of organizational achievement (Faraj et al. 2011) but also creates additional demands for group functioning (Dougherty and Dunne 2012; Weick 1985).

Virtual teams face distinctive managerial and operational challenges (Martins et al. 2004). All interactions require time, energy, and cognitive resources, and development of effective group processes comes with a communication overhead (Macmillan et al. 2004). Virtual team communication is leaner (Daft and Lengel 1986) than is face-to-face interaction. Working collaboratively without face-to-face interaction and conventional social cues can increase levels of conflict and compromise team cohesiveness (Kankanhalli et al. 2006; Polzer et al. 2006). Primarily-virtual work groups need social mechanisms to compensate for sparser interactions (Sproull and Kiesler 1986).

Effective global virtual teams attended to relationship-building activities as well as coordination and boundary spanning (Maznevski and Chudoba 2000). Conflict and trust are both key variables in the functioning of teams with distributed membership (Montoya-Weiss et al. 2001). The importance of social interaction and relationship building among virtual team members is well-recognized (Martins and Schilpzand 2011). Yet virtualness presents challenges for teams with respect to building interpersonal trust (Jarvenpaa and Leidner 1999) and cognition-based trust (Kanawattanachai and Yoo 2007). Trust is an important ingredient for effectiveness in all work groups, but is perhaps more so for virtual teams contending with the social deficiencies of physical separation (Jarvenpaa et al. 1998).

On the other hand, such social deficiencies may have a silver lining in the form of minimizing status hierarchy (Anderson et al. 2007; Dubrovsky et al. 1991), and the nature of asynchronous communication allows team members to contribute when their schedule permits (Straus 1996). Equality of participation is a driver of team effectiveness (Mesmer-Magnus and DeChurch 2009) and improved decision making (Locke et al. 1997). Participation dynamics are an important element of virtual communication research as evidenced by the proliferation of studies on this topic in computer-mediated communication and collaborative electronic environments (Benbasat and Lim 1993; Burke and Chidambaram 1995; Desanctis and Gallupe 1987; Valacich et al. 1994).

Related to participation, other action processes on which the virtual team effectiveness literature has focused in the past decade are coordination, communication, and knowledge integration (Gilson et al. 2015; Kock and Lynn 2012). Virtual teams have a definitive edge with regards to the diversity of team member knowledge (Martins and Schilpzand 2011) in that geographic location or organizational affiliation are not constraints on assembling the individuals best-suited to the team's focal task (Townsend et al. 1998). Virtual teams also afford more fluidity of membership suggesting that members with specific expertise could be added based on task demands (Kirkman et al. 2004). But digital coordination of team members' knowledge presents distinctive challenges (Faraj and Sproull 2000). While benefits of structural diversity in teams may outweigh potential coordination costs (Cummings 2004; Reagans and Zuckerman 2001), mechanisms of coordination and agility for digitally-driven teams need scholarly attention (Sarker and Sarker 2009). Team capabilities for integrating relevant knowledge are more difficult to develop when interactions are digitally enabled (Robert et al. 2008). One key coping mechanism can be adaptation of technology use to fit various stages of team development and task demands (Thomas and Bostrom 2010).

Knowledge transfer within and across groups plays a fundamental role in organizational effectiveness (Argote et al. 2000). Electronically-mediated communication creates hurdles for the exchange of complex, tacit knowledge (Griffith et al. 2003). Consequently, individual team members have a greater cognitive burden in accessing collective knowledge and arriving at shared understandings (Cramton 2001). Emergent group mind has been explained with the concept of a transactive memory system, the coordination amongst team members in storage and retrieval of distributed knowledge (Wegner 1987). Critical to the development of team transactive memory is participants' prior familiarity, or at least opportunities for rich communication in the early phases of a team lifespan (Lewis 2004). Virtual development of a transactive memory system may require more time and effort (Kanawattanachai and Yoo 2007), although researchers have also observed that virtual teams have relatively shorter lifespans (Jarvenpaa and Leidner 1999). The extent of virtualness or the presence of colocated member subgroups may impact team development and outcomes (Polzer et al. 2006).

2.1.1 Virtual Teams and Time

Teams evolve over time (Gersick 1988). Understanding collaboration and other team-level phenomena requires examination of temporal dynamics (Kozlowski and Bell 2003; Marks et al. 2001). The use of email and other asynchronous media creates a time lapse between a team member's contribution and feedback from others in the group (Hinds and Bailey 2003; Mannix et al. 2002). Yet relatively few studies of virtual teams have incorporated time (Martins et al. 2004) and more longitudinal work is needed (Gilson et al. 2015). Noteworthy longitudinal studies of virtual teams have explored: benefits of an online feedback system (Geister et al. 2006), the nature of interactions shaped by hierarchical and geographical boundaries (Metiu 2006), transparency of team member activities as an antecedent to trust (Goh and Wasko 2012), and improvements over time with respect to team member satisfaction as well as social information challenges presented by virtual interactions (Chidambaram 1996). A study of virtual MBA teams over eight weeks found that communication related to the task was important during early stages of virtual team work, but task coordination was the best predictor of performance in later cycles (Kanawattanachai and Yoo 2007).

2.2 Innovation Teams

2.2.1 Innovation Team Processes

All teams engage in dynamic activities of coordinating in the face of uncertainty (Edmondson 2012); risk and ambiguity are particularly potent for innovation teams (Buijs 2007). Innovation – the design and development of new products, services, and systems – is driven by individual socio-cognitive abilities (Hevner et al. 2004) as well as the nature and periodicity of group social processes (West 1990; West and Anderson 1996). Team-level innovation is a function of ongoing interpersonal discussion (King and Anderson 1990) and may be conceptualized as a set of collaborative, information-processing activities (Moenaert et al. 2000). A meta-analysis of 104 studies over thirty years found team process variables such as communication and cohesion to be consistently associated with innovation outcomes (Hülsheger et al. 2009).

Research on creativity and innovation in teams has explored influences of the focal team task, team member composition, and the extent to which team members can integrate diverse knowledge to bring about innovation (West 2002). Successful innovation requires mechanisms for interaction that effectively leverage individual and collective team resources (Majchrzak et al. 2012). Innovation teams face several layers of complexity in structure, scope, and sequencing (Markus et al. 2002). Innovation processes are inherently non-routine, drawing on multiple bases of knowledge and experience (Edmondson and Nembhard 2009). Generation of new ideas and repurposing of existing ideas occur through interactions of individuals with diverse but overlapping pools of knowledge (West 1990). The literature on diversity in organizations is itself diverse (Klein and Harrison 2007). Variety, referring to differences in relative experiences as well as distinctive information, is the facet of diversity most associated with creativity, innovation, and work group flexibility (Harrison and Klein 2007). Yet assembling a high-variety multidisciplinary team is not sufficient for successful innovation because not all diverse teams effectively leverage information resources (Webber and Donahue 2001).

2.2.2 Innovation Process Phases

Innovation is often described as a series of phases in idea development that evoke distinctive challenges, knowledge requirements, and cognitive processes (Basadur and Gelade 2006; Boeddrich 2004; Tushman 1977; Veryzer 1998). Each stage of innovation culminates in an evaluation process followed by abandonment, adaptation, or adoption of aspects of the idea as appropriate (Buijs 2007). Diversity of team member knowledge is important for creativity (Ancona and Caldwell 1992), the first step towards an innovative idea. But diversity of knowledge and skills are also important in post-generative phases of innovation (Anderson et al. 2014). Few individuals excel at both idea generation and implementation (Gutnick et al. 2012; Miron et al. 2004), one explanation for the prevalence of teams as a strategy for innovation and new product development. Successful innovation teams need capabilities for generating new ideas as well as enacting those ideas and selling them to peers, lead testers, and eventually end-users. A study of new product development teams illustrated the intricacy of innovation: poorly-performing groups did not differ with regards to idea generation but with how they presented and implemented those ideas (Erez 2012). A successful innovation enterprise is often closely linked to or embedded in communities-of-practice (Brown and Duguid 1991), collaborative learning networks that serve to test and refine team-developed ideas and prototypes (Gloor 2006).

Innovation entails not just the discovery and articulation of new ideas but also cycles of synthesis, evaluation, tinkering, and hardwiring of ideas into targeted systems (Arthur 2009; de Bono 1992; Hargadon and Douglas 2001; Kanter 2000). Thus the group structures and interaction dynamics best-suited for generative phases may not thrive during later periods of testing and development. As goals, tasks, and resources shift, effective innovation teams must respond accordingly. Developing new ideas and products happens over a period of time, so assessment of innovation team performance should also be longitudinal (Leenders et al. 2003).

2.3 Opportunities and Challenges for Virtual Innovation Teams

Existing knowledge about virtual innovation teams is fragmented across several literatures, but when considered collectively previous studies present knowledge integration and implementation as the central quest of virtual innovation teams. Complexity of tasks and goals, uncertainty inherent in innovation processes, and digital communication demands shape the distinctive challenges facing virtual innovation teams. The nature of virtual collaboration is both advantageous and problematic for teams targeting innovation.

Creative teams need extensive ties, expandable tiers, and exchangeable membership (Ancona and Bresman 2007). Virtualness affords agility (Sarker and Sarker 2009) and fluidity via reconfigurable structures (Desanctis and Monge 1998). Teams require effective feedback loops to manage the need for evaluative iteration in idea development (Anderson and West 1998). Yet physical separation delays timely feedback (Martins and Schilpzand 2011). That virtualness can thwart the maintenance of positive relationships (Jarvenpaa and Leidner 1999) is concerning because interpersonal trust is particularly important for managing uncertainty inherent in the unchartered territory facing innovation teams. Communication overhead (Macmillan et al. 2004) and coordination costs can compromise virtual collaboration (Cummings et al. 2009).

Complex team tasks demand more effective communication but task interdependence can actually improve virtual team performance (Chi et al. 2012). The digital modes of virtual teams are advantageous in that electronic communication creates a codified record of team interactions (Martins et al. 2004), which might be reviewed, copied, aggregated, searched, edited, and/or transmitted externally (Kane et al. 2014). Distributed teams have to overcome hurdles to virtual information processing and work harder to integrate knowledge of individual team members (Robert et al. 2008). Engagement of all team members plays a role in team innovation (Drach-Zahavy and Somech 2001) as well as virtual team effectiveness (Straus 1996).

Psychological safety, a “shared belief that the team is safe for interpersonal risk taking” (Edmondson 1999: 354), is essential for collaborative learning and team effectiveness (Edmondson 2002). Psychological safety is an important antecedent of creativity, which makes sense given the risk associated with generating novel ideas (Baer and Frese 2003; Kark and Carmeli 2009). High-quality interpersonal relationships and psychological safety are associated with organizational learning, particularly with learning from failures (Carmeli et al. 2009), one element of successful rapid iterative testing associated with successful innovation endeavors (McKee 1992). Furthermore, psychological safety may be important in building trust in virtual teams and helpful to overcome sparse interactions online that can hinder the flow of knowledge resources in a communication network (Cordery and Soo 2008; Griffith and Neale 2001). Trust and psychological safety are elements of virtual innovation team interactions that could constrain or enable equality of participation. Participative safety was a determinant of team innovation levels (Burningham and West 1995) as well as the number of innovations generated and team perceptions of innovativeness (Anderson and West 1998). Comparable levels of team member participation seem to offer both cognitive and interpersonal advantages and is particularly important for team success in defining aims and generating shared commitment (Erez et al. 1985).

2.3.1 Information Elaboration and Knowledge Integration

If new social connections and knowledge permutations are good for innovation (Obstfeld 2005), malleable structures and fluid membership associated with virtual teams could be especially useful in an innovation setting. Virtual teams lack shared institutional inertia and can potentially access a broader pool of human and information resources (Martins and Schilpzand 2011), advantages for teams developing new ideas given the combinatorial nature of innovation (Tuomi 2002; Yoo et al. 2012). Innovation work draws on multiple bases of knowledge and experience (Leenders et al. 2003), implying that variety with respect to team members' experiences and knowledge bases is an advantage for virtual innovation teams.

Innovation teams face ambiguity with respect to optimal application of team members' knowledge and experience (Pasmore 1997). The challenges of knowledge integration are more pronounced both when teams are diverse and managing novelty (Majchrzak et al. 2012), suggesting that diversity of information resources are helpful only to the extent that virtual innovation team members are able to share and integrate what they know. The degree to which team information resources are shared and effectively processed at the group level is known as *information elaboration* (Van Knippenberg et al. 2004). This mechanism of elaboration links diversity of perspectives and information resources amongst team members to enhanced team functioning (Homan et al. 2007) and has been positively associated with team performance in team diversity research (Meyer et al. 2011). Information elaboration "enables functionally diverse teams to transform their breadth of knowledge resources into actionable solutions" through an open exchange of task information, reflection and clarification on perspectives of others, and integration of perspectives at a higher level (Resick at al. 2014: 165). While functionally diverse teams can derive the most benefit from these intensive information processing activities, they are least likely to engage in them (Mesmer-Magnus and DeChurch 2009).

2.3.2 Virtual Innovation Team Networks

Social capital (with structural, relational, and cognitive dimensions) refers to resources embedded in group connections (Nahapiet and Ghoshal 1998). While each dimension of social capital supports collaboration, structural and cognitive capital were more important for knowledge integration when teams interacted through lean digital networks than when they communicated face-to-face (Phelps et al. 2012; Robert et al. 2008). Kane and Borgatti (2011) explored the relationship between group-level social capital and collective capabilities to effectively harness group resources; they found centrality and embeddedness of individuals with particular expertise to be a key factor. Social capital, "resources embedded in a social structure that are accessed and/or mobilized in purposive action" (Lin 2001, p. 29), has been widely considered as network-based phenomena (Adler and Kwon 2002; Burt 2005; Gordon et al. 1997; Reagans and Zuckerman 2001; Tsai 2000). Consideration of social capital as “the information, trust, and norms of reciprocity inherent in one's social networks” (Woolcock 1998, p. 153) suggests that group network structures are key in understanding the nature of effective collaboration (Cummings and Cross 2003) amongst diverse and dispersed virtual team members.

The structure of a virtual team’s communication network is a potential mechanism for knowledge integration. The impact of individual team member network structures on virtual team communication has been examined (Sarker et al. 2011) but fewer studies have considered network structure at the group level. The study of patterns in a team communication network that emerge from individual-level interactions could contribute to understanding of team collaboration (Balkundi and Harrison 2006). A network-based approach could be particularly enlightening with respect to what we know about effectiveness of virtual teams (Gilson et al. 2015).

2.4 Observing Virtual Collaboration with Social Network Analysis

2.4.1 Observing Virtual Collaboration

Thus far we have motivated the study of virtual innovation team dynamics and outlined what is known on relevant research fronts. In the rest of this chapter we consider methodological issues for the study of virtual innovation teams and propose social network analysis as an approach to observe phenomena underlying virtual work.

Managerial and scholarly emphasis on canonical work routines may overlook self-organized processes and emergent relationships, which often differentiate exceptional teams and organizations (Brown and Duguid 1991; Carley and Ahuja 1999). Julian Orr (1987, 1990), a pioneer in investigating non-canonical aspects of organizations, used conventional ethnographic methods relying on the five senses to observe working, learning, and innovating in a community-of-practice. This community was not formally acknowledged by the home corporation yet instrumental in the accomplishment of its mission. Management scholars have recognized both formal structures and emergent routines as a key source of organizational intelligence (Feldman and Pentland 2003). Today a researcher is likely to find earthbound ethnographic methods (rooted by direct observation in the physical universe) deficient to study digitally enabled interactions occurring online and on screens (Jordan 2012; Riopelle 2012; Weick 1985). The study of emergent work processes in modern organizations presents new challenges and compels both conventional and digital ethnography (Murthy 2008).

2.4.2 Social Network Analysis

A network is a pattern of interconnections among a set of entities (Easley and Kleinberg 2010). The previous section introduced social capital and other network concepts associated with virtual innovation teams. A network-based methodological approach is helpful to envision the ebb and flow of resources and boundaries in collaborative innovation networks (Gloor 2006; Kolleck 2013). Network structure is important when considering group interactions or other socially-driven, organizational phenomena (Brass et al. 2004; Valente 2012). Visualization and characterization of network structures accentuate underlying work processes and interactions (Haythornthwaite 1996). For example, this study suggests that successful innovation teams with distributed members are enabled by communication network structures that complement the fluid nature of virtual knowledge collaboration (Faraj et al. 2011).

Social network analysis (SNA) is an established approach to study workplace interactions and detect behavioral signals (Borgatti and Foster 2003; Cross et al. 2002) offering a robust set of tools to model the social context of innovations and their diffusion (Kolleck 2013). SNA consists primarily of mapping the locations of entities and presence/intensity of relationships between entities onto a network graph with statistical properties (Scott 2012). SNA has conventionally involved secondary data collection relying on perceptions of recognized network actors (Carrington et al. 2005; Marsden 1990). Advances in connectivity and computational power have created opportunities to visualize networks of knowledge flows and communication structures underlying digitally enabled collaborative work (Watts 2007). Each time that we send an email or interact online we create "digital traces" of communication behaviors as well as information and ideas (Lazer et al. 2009). These traces may be used to create models of social networks and to analyze patterns of interaction at ever-increasing levels of scale (Agarwal et al. 2008).

Email messages are one primary source of digital data used to model social networks (Kidane and Gloor 2007; Quintane and Kleinbaum 2011; Van Alstyne and Zhang 2003). The use of email and other digital traces for SNA seems particularly appropriate for the study of virtual teams. Email correspondence enables work without a shared physical setting (Finholt and Sproull 1990), and it effectively models the informal interactions that characterize modern virtual organizational forms (Monge and Contractor 2001; Wellman 2001). Research spanning half a century has established that study of group interactions and communication can reveal informative structural patterns (Brass 1985; Burt 1980; Cross et al. 2002; Gloor and Zhao 2004; Granovetter 1973; Nadel 1957; Nohira and Eccles 1992; Phelps et al. 2012). Following Ahuja and Carley (1999), this study conceptualizes virtual team structure as "arrangement of differentiated elements that can be recognized as the patterned flows of information in a communication network" (Rogers and Kincaid 1981, p. 82). Empirical innovation studies drawing on SNA are relatively few notwithstanding widespread recognition of the value of a network-based approach in modeling the social context around development and diffusion of innovations (Kolleck 2013).

2.5 Literature Review Summary

This chapter has summarized the literatures on virtual teams and team-level innovation. The "digital workforce" is emerging across temporal and spatial boundaries in diverse industries and social contexts (Colbert et al. 2016: 731). Virtual teams are evermore a basic unit of analysis for modern collaborative work (Suh et al. 2011). Innovation teams must make sense of the world as it unfolds and participate in enacting its next state as do all working groups (Weick et al. 2005), but the novel and evolutionary qualities of innovation work create a thicker veil of uncertainty under which they must operate (Edmondson and Nembhard 2009).

The juxtaposition of these research streams reveals distinctive opportunities and challenges for virtual teams seeking to innovate. We present a network-based methodological approach as a strategy to explore virtual innovation team collaboration and to test the hypotheses that presented in the following chapter along with our research model.

CHAPTER 3: THEORY DEVELOPMENT

There is a need for enhanced understanding of how collaborative structures impact processes and outcomes for virtual teams and innovation teams. This chapter will outline our theorization about network structures and communication dynamics with six hypotheses, visually summarized in Figure 1. We consider team centrality, structural dynamics, and participation equality as potential drivers of virtual innovation team outcomes: work group performance and radical innovation.

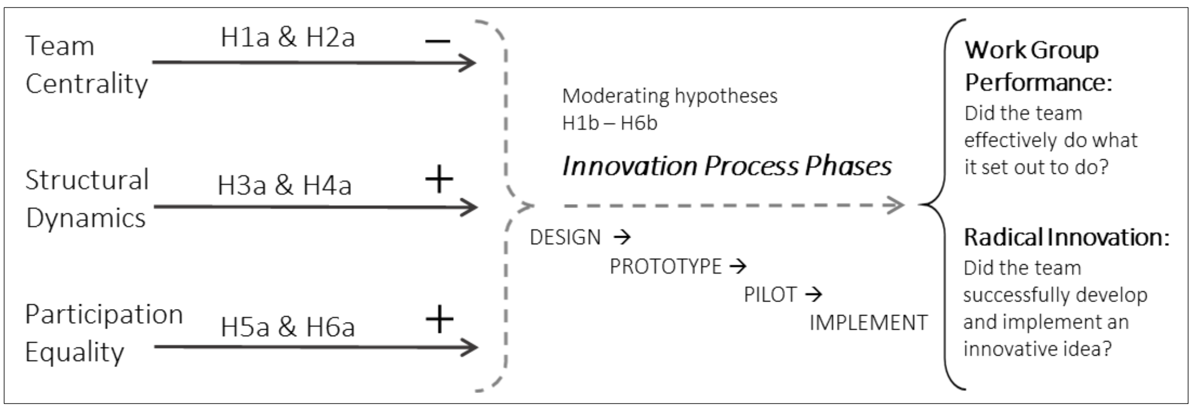


Figure 1: Theoretical Model

3.1 Network Structures

Patterns of connections amongst team members may be conceptualized as social network structures. These structures may constrain or enable interactions and thus the flow of information and other resources (Balkundi and Harrison 2006). Network structures represent underlying social dynamics and may be highly influential in shaping team processes and performance (Cummings and Cross 2003; Phelps et al. 2012; Sparrowe et al. 2001). How teams communicate turns out to be an important predictor of success (Gloor 2006), as important as all other team inputs combined and more important than the content of team discussions (Pentland 2012). Communication network structures can serve as mechanisms to address challenges of knowledge coordination and to manage the uncertainties facing virtual teams (Suh et al. 2011) and innovation teams (Tsai 2001).

Team accomplishments are partially a function of the skills and knowledge of individual team members, but more essential is the extent to which they collectively identify relevant resources and put them to work (Edmondson 2012). Structure is essentially how the interdependency of team components and emergent processes shape the actions of its members. Team and other organizational structures fall along a continuum between institutional formality and informal emergence (Carley and Ahuja 1999). As modern organizations become increasingly virtual, examination of informal social structures that emerge amongst collaborators may become increasingly more informative. For example, informal network ties were better predictors of knowledge exchange than were formal project team structural variables (Behrend and Erwee 2009). Similarly, the centrality of position within a knowledge network explained more variation in individual innovative performance than did formal organizational roles (Ibarra 1993).

Network models use structure to convey how information and resources are distributed in groups (Burt et al. 2013). An individual's network position may represent their capacity for connectivity to others, the extent of their access to collective resources, and/or their propensity to exhibit certain behaviors or engage in particular activities (Phelps et al. 2012). For example, density (representing interconnectivity) in the social networks of individual engineers predicted their involvement in innovation at an automotive manufacturing organization (Obstfeld 2005). Direct links to other individuals facilitate communication and knowledge sharing more so than indirect links (Singh 2005), but weaker ties can be sources of novel information (Granovetter 1973). Consideration of optimal network structures is contingent on context: some configurations may be ideal for information diffusion but hostile to knowledge integration activities within a distributed team (Cummings and Cross 2003).

3.2 Network Centrality

Centrality is a key element in conceptualization of individual and group network structures (Borgatti and Everett 2006; Ibarra 1993). A central network position provides timely access to information and potentially more opportunities to leverage shared resources (Burt 1992). Centrality is closely linked to social capital for both individuals and groups (Adler and Kwon 2002; Burt 2005), but advantages presented by a central network position depend on characteristics of the network (Owen-Smith and Powell 2004) and the node (Kane and Borgatti 2011; Mehra et al. 2001). Centrality may refer to different structural characteristics of a network node; these characteristics include degree (the number of direct connections), closeness (representing distance from connections), and betweenness (indicating location in a network and the extent to which it connects other nodes) (Valente et al. 2008).

The choice of a centrality measure depends on the aim of its application (Freeman 1979). This research will examine betweenness centrality because we are primarily concerned with the flow of information and knowledge resources amongst team members (Borgatti 2005).

Betweenness centrality, representing the extent to which an individual's network position spans connections between other individuals, is a useful measure of individual capacity to efficiently locate and apply relevant knowledge (Mehra et al. 2001).

3.2.1 Team Centrality

Team centrality represents variation in levels of individual team member centrality (Sparrowe et al. 2001). We consider team centrality as emblematic of the extent to which one or a few team members dominate interactions by connecting other team members not otherwise linked or perhaps weakly connected (Freeman 1977). For a virtual team, high team centrality signals hierarchical communication flows while lower levels of team centrality suggest direct connections between participants with fewer intermediaries (Scott and Carrington 2011). While some simple team-based tasks might benefit from highly centralized structures, research suggests that decentralized communication is preferable for complex tasks and information diffusion (Rogers 2010; Shaw 1964). Centralized team structures imply that information must be funneled through particular levels for the purposes of decision making (Carley and Ahuja 1999).

Virtual teams and/or innovation teams may derive particular benefits from low levels of team centrality. Firm-level research indicates that a fast-paced environment is best navigated with lower levels of organizational structure (Davis et al. 2009). A study of teams engaged in complex, non-routine project work indicated that centralized team structures can obstruct lateral communication and inhibit performance (Cummings and Cross 2003). Lower levels of communication centralization supported creative processes for new product development teams (Leenders et al. 2003). Collaborative innovation networks, groups of self-motivated individuals leveraging individual and shared resources in pursuit of a common goal, are fueled by ethical codes, trust, and decentralized control (Gloor 2006). Therefore, we predict:

Hypothesis 1a: There will be a negative relationship between team centrality and virtual innovation team performance.

Hypothesis 2a: There will be a negative relationship between team centrality and radical innovation.

3.2.2 Team Centrality by Innovation Process Phase

The impact of any relationship between team centrality and performance is likely to vary throughout the lifespan of an innovation project. The negative direction of the association may be more pronounced in early generative stages. Innovation teams need both creativity to generate new ideas and operational efficiency to develop and implement those ideas that are feasible (Obstfeld 2005). Because innovation processes demand different sets of skills and cognitive schema, teams may need to respond with both highly-central communication and decentralized individual work (Kidane and Gloor 2007). High team centrality seems likely to map to decisive action or pooling of resources for a concerted effort. A decentralized structure seems well-suited to support idea generation through inclusiveness and facilitation of diverse information sources.

One study of temporal aspects of virtual efficacy compared the criticality of task-based communication in early phases of team development to the increased need for knowledge coordination later on (Kanawattanachai and Yoo 2007). The operative challenge for teams is to find the right balance between “creativity of emergence and stability of design” (Capra and Luisi

2014, p. 320). We propose that the negative relationship between team centrality and innovation outcomes may vary during different phases of the innovation process:

> *Hypothesis 1b: Innovation process phase will moderate the negative relationship between team centrality and virtual innovation team performance.*

> *Hypothesis 2b: Innovation process phase will moderate the negative relationship between team centrality and radical innovation.*

We anticipate that low centrality is most essential for teams in earlier phases of innovation. Thus the negative impact of centrality seems likely to diminish over the innovation team lifespan.

3.3 Structural Dynamics

It is intuitive that the relationship between team centrality and team outcomes will change over time along with the demands of the innovation process. But perhaps change itself supports the productivity and effectiveness of virtual innovation teams. This study will explore how *structural dynamics* – the extent of change in centrality structures over time – impacts team performance and innovation.

3.3.1 Structural Dynamics of Team Centrality

While teams with distributed members and resources have potential to destabilize, agility is a defining advantage of virtual teams (Sarker and Sarker 2009). And agility could be a core competency of innovation teams working to accommodate changing and sometimes conflicting specifications of managers and end-users (Bledow et al. 2009). Ashby 's (1956) idea of *requisite variety* suggests that an organization's internal composition must keep pace with the complexity of its external environment. To “remain fit, survive, and thrive” organizational structures “co-evolve with the dancing, rugged competitive landscape” (Tanriverdi et al. 2010, p. 828). Fluid teams with adaptive reserve may take on horizontal, malleable structures and also change those structures often (Nonaka and Takeuchi 1995).

Frequent changes in team centrality may signal dynamics of meritocracy in which decision making and other leadership activities rotate amongst different team members as a function of their expertise and its fit to demands of the work. If a peripheral team member has pertinent knowledge valued by others, network structures reconfigure around them (Perry-Smith and Shalley 2003). Individual centrality may change because a team member intensifies his or her communication behaviors, assumes a leadership role, or becomes an “information broker” or hub for task-relevant knowledge (Cross and Prusak 2002: 10). In prior work based on e-mail network analysis, Kidane and Gloor (2007) found that oscillating levels of centrality predicted higher levels of team creativity, while steady levels of centrality predicted high productivity. We anticipate that shifts in levels of team centrality over time are characteristic of thriving virtual innovation teams:

Hypothesis 3a: There will be a positive relationship between structural dynamics and virtual innovation team performance.

Hypothesis 4a: There will be a positive relationship between structural dynamics and radical innovation.

3.3.2 Structural Dynamics by Innovation Process Phase

Just as the optimal *level* of team centrality seems likely to vary across time and phases of innovation, so does the extent of *fluctuation* in team centrality. The contrast between activities and challenges associated with a generative design phase and those in an evaluative testing phase suggest that we might expect a similar divergence across phases with respect to our hypothesized positive effects of structural dynamics. Assuming that fluctuation in team communication network structures is a signal for adaptive capacity, consideration of dynamism as an asset follows from what we know about innovation processes and virtual work.

The permeability of organizational boundaries and fluidity with respect to membership and other resources suggest that adaptation is essential for high-functioning virtual teams (Wageman et al. 2012). Effective teams recognize learning opportunities (including innovation process failures) as they emerge and have the dexterity to accommodate changing circumstances (Edmondson 1999). Cross-functional teams facing novel situations can transcend their knowledge differences through cyclical interactions that serve to integrate individual contributions and repeatedly modify solutions (Majchrzak et al. 2012). Accordingly, we predict that the association between structural dynamics will vary as a function of innovation process phase:

Hypothesis 3b: Innovation process phase will moderate the positive relationship between structural dynamics and virtual innovation team performance.

Hypothesis 4b: Innovation process phase will moderate the positive relationship between structural dynamics and radical innovation.

We anticipate that structural dynamics are likely to be most potent in the earlier phases of innovation; thus the positive relationship predicted seems likely to diminish during pilot testing and implementation.

3.4 Participation Equality

While structure is a basic functional element of all teams, the “vehicle of new product development is communication” (Leenders et al. 2003: 70). Research suggests that members of exceptional teams talk and listen in equal measure whereas lower-performing teams might have dominant members, or members who primarily talk or listen (Pentland 2012). *Participation equality* on a virtual innovation team implies evenly distributed task activities and comparable levels of initiative amongst team members as evidenced by balanced communication behaviors. High-performing teams (working both online and face-to-face) communicate frequently and participate equally (Woolley et al. 2015).

3.4.1 Virtual Innovation Team Participation

The nature of virtual collaboration seems to support symmetry with respect to team member contributions. Electronic media use increases participation by team members who might be more reserved in a face-to-face collaborative environment (Jarvenpaa et al. 1988; Martins et al. 2004). Diminished social cues can present coordination and interpretative challenges but reduce status differences between collaborators in ways that support participation equality (Hollingshead 1996).

New organizational designs that support collaboration are based on three main elements: actors who self-organize, commons where actors share resources, and infrastructures that enable collaboration (Fjeldstad et al. 2012). Creative teams, new product development units, and other functional groups engaged in emergent knowledge-intensive processes are primarily self-organizing (Barker 1993; Markus et al. 2002). Proportionality of team members’ communication behaviors may be an indicator of team mechanisms for self-organization that result in effective pooling of individual abilities and shared understandings of how to leverage team resources towards a common goal. As the variation in team members' communication behaviors decreases – demonstrative of symmetry with respect to the frequency and intensity of team member participation – innovation team functioning will improve (or so we predict):

Hypothesis 5a: There will be a positive relationship between participation equality and virtual innovation team performance.

Hypothesis 6a: There will be a positive relationship between participation equality and radical innovation.

3.4.2 Participation Equality by Innovation Process Phase

We have suggested that teams are well-positioned to innovate when members' communication behaviors are balanced. This relationship between participation equality and performance is likely to change over time alongside shifting demands in different phases of the innovation process. An essential aspect of bridging the gaps of time and space for teams is the fit of interactions to relevant tasks as well as the sequencing of communication patterns (Maznevski and Chudoba 2000). Teams operating over time encounter a wider scope of challenges which may be different from those they tackled early on (Woolley et al. 2015). If knowledge requirements are changing throughout the lifespan of idea development, it seems logical that communication patterns of teams would also change. Expertise location, or the extent to which team members know how others can contribute to particular knowledge requirements, can improve team performance (Faraj and Sproull 2000). High volume of communication was important for virtual teams of MBA students in the formation of expertise location and in building trust; yet once teams were established, deeper exchanges of knowledge were more important than the frequent task-oriented interactions that characterized thriving virtual teams in early stages (Kanawattanachai and Yoo 2007).

It seems that participation equality may be most important in early phases of the innovation process in which creativity and idea generation are paramount. Counting the number of ideas generated is key in predicting the ability of a group to develop creative solutions (Simonton 1999). Theories of team creativity advocate for interpersonal discussion amongst team members (King and Anderson 1990) and recombination of current knowledge through ongoing interactions as mechanisms for generating innovative ideas (West 1990). The challenges facing innovation teams in later phases may also be best-approached by teams with high participation equality, but the theoretical connection between balanced communication behaviors and generativity associated with early innovation processes is stronger than that in later phases. The impact of participation equality on virtual innovation team outcomes seems likely to vary as a function of innovation process phase:

Hypothesis 5b: Innovation process phase will moderate the relationship between participation equality and virtual innovation team performance.

Hypothesis 6b: Innovation process phase will moderate the relationship between participation equality and radical innovation.

We anticipate that the positive relationship between participation equality and performance will diminish throughout phases of the innovation process.

3.5 Theory Development Summary

This chapter has outlined our theory development and research model. We hypothesized that variation in team centrality, structural dynamics, and participation equality may be associated with variation in team performance and radical innovation. We also considered the extent to which these relationships, if present, might vary over time and/or in different stages of the innovation process. We hope to contribute to understanding of interaction dynamics in virtual innovation teams by testing these hypotheses and evaluating the extent to which our predictions hold up. The following chapter will describe the research context in which our theories were tested as well as methods employed for data collection and analysis.

CHAPTER 4: RESEARCH METHODS

This chapter will describe our research context, data sources, and methodological design choices. We tested our hypotheses by analyzing variation in the email communication networks of eleven virtual innovation teams collaborating under the auspices of a large-scale health care system design project. Data were collected from digital archives of team email correspondence and from ratings of team performance outcomes from senior leadership of the project.

4.1 Research Context

Health care delivery systems are in desperate need of innovation (Berwick et al. 2015; Berwick and Hackbarth 2012; Margolis and Halfon 2009; Zuckerman et al. 2013). Our study of virtual innovation team dynamics occurred in the context of a large-scale health care innovation project. The Collaborative Chronic Care Network (C3N) Project proposed to design, develop, and test a learning health care system (Olsen et al. 2007) using inflammatory bowel disease (IBD) as a pilot condition (Margolis et al. 2013) on which future networks might be modeled (Forrest et al. 2014). Project funding originated with a National Institutes of Health Transformative Research grant, part of the NIH Roadmap initiative focused on bold projects that have potential to transform a field of science.

Guided by project visionaries, project collaborators – to become co-designers of a new chronic care system – developed a portfolio of social, scientific, and technical innovation sub-projects (Gloor et al. 2012; Seid et al. 2014). Teams were largely self-organizing within the shared context of the C3N Project. The project functioned as a sort of incubator providing funding and other resources as well as the opportunity for knowledge collaboration across the cluster of team sub-projects. The C3N Project was coordinated by Cincinnati Children's Hospital Medical Center (CCHMC), where the majority of C3N Project collaborators were based. The project had a strong virtual component with collaborators from multiple institutions based in at least fifteen U.S. cities and several based in Europe.

The five-year project grant period concluded in September 2014. Since then, the C3N model has extended to shape networks targeting better care systems for patients with cystic fibrosis and pediatric rheumatology. We observed eleven innovation teams affiliated with the C3N Project over twenty-three months (September 2012 to July 2014) engaging in the development of new products and services and platforms targeting better health, care, and costs for children and adolescents with chronic diseases. Table 1 contains descriptive statistics and other summary information for each team. Table 2 describes the focal innovation for each team.

Our approach to selection of the eleven teams observed in this study is described in the following section on data sources and study participants. The project was organized such that participating teams were to a certain extent interdependent, but we conducted statistical tests for the effects of interdependence and use methods to accommodate it when necessary, as detailed later in this chapter along with diagnostic tests. Description of measures, model variables, and analytic procedures will follow to end the chapter.

	Team name	Team size	Core team size	% of core mailboxes collected	% co-located members	Member tenure (months)	% female members	Network actors	Network connections	Average Network Density
1	Communications	12	4	75%	30%	16.2	69%	10.2	1,144.0	0.67
2	Enhanced Collaboration System	15	5	80%	59%	17.4	46%	7.3	288.1	0.42
3	EMMA App	9	5	20%	37%	11.4	44%	5.7	147.2	0.66
4	IBD Volunteers	6	4	75%	94%	9.2	63%	5.0	110.7	0.58
5	ICN Exchange	16	10	70%	67%	13.8	63%	12.0	1,623.4	0.57
6	Patient Advisory Council	6	4	75%	36%	18.9	100%	5.6	1,365.6	0.91
7	Passive PRO	11	4	75%	36%	17.2	37%	8.8	668.7	0.51
8	Personalized Learning System	15	7	57%	37%	15.5	41%	13.4	1,451.3	0.48
9	Population Management & Pre-Visit Planning	12	5	20%	26%	12.4	48%	7.8	163.7	0.46
10	Clinical Team SNA	7	3	33%	46%	16.1	27%	6.6	347.4	0.64
11	YouMeIBD	13	5	60%	71%	18.3	7%	5.8	53.8	0.69
	TEAM AVERAGE	**11.1**	**5.1**	**56.5%**	**48.7%**	**15.1**	**50%**	**8.3**	**669.4**	**0.6**

Table 1: Virtual innovation teams (n = 11)

C3N Project Team		Description of Team Innovation
1	Communications	Develop strategies and tools to foster awareness and engage the IBD care community and to track online trends for C3N narrative.
2	EMMA App	IPad game for patients as transition tool in a clinical setting; helps providers evaluate gaps in knowledge of disease management.
3	Enhanced Collaboration	Automated platform to support patient and family care management through symptom tracking and personalized feedback.
4	IBD Volunteers	Development of a patient-driven peer mentoring program for IBD patients.
5	ICN Exchange	Online knowledge sharing platform for community of pediatric gastroenterologists and clinicians, researchers, parents and patients.
6	Patient Advisory Council	Working group of pediatric IBD patients committed to collaboration with clinicians, researchers and other care delivery partners.
7	Passive PRO	Mobile sensing technology for passive patient-reported outcomes (PRO) and tracking of behavioral signals to support individualized care plans.
8	Personalized Learning System	Multi-user platform for personalized experimentation, data collection, symptom tracking, and clinician-patient-parent collaboration.
9	Population Management & Pre-visit Planning	Enable risk stratification of patient population and timely pre-visit preparation to optimize patient-provider encounters.
10	Care Team SNA	Intervention to assess quality improvement networks within pediatric gastroenterology centers and inform design of care delivery teams.
11	YouMeIBD	Facebook application using a matching algorithm to connect IBD patients for social support and knowledge sharing about disease management.

Table 2: Virtual innovation teams with innovation project descriptions

4.2 Data and Participants

4.2.1 Data Sources Summary

We approached this research with observations from two primary sources: team ratings and archival data. We used questionnaires to collect team outcome ratings from project senior leaders on a bi-monthly to quarterly basis during the observation period. Discussion of the rating process will follow in this chapter along with presentation of response variables. We used archival data from project monthly reports to track teams' progress with respect to the innovation process in four phases. Digital archives of project email correspondence were our primary source of data. Discussion of the email data collection process will follow in this section after introduction of study participants.

4.2.2 Study Participants

Study participants (*n = 20*) were employees of CCHMC who were active members of one or more of the C3N Project innovation teams in this study. Participants are listed in Table 3 by professional role and team affiliations. Voluntary participants indicated their decision to join the study via verbal consent and the provision of mailbox access to the CCHMC research coordinator who supported this research.

	Study Participants by professional role	C3N team affilia-tions	Team 1	Team 2	Team 3	Team 4	Team 5	Team 6	Team 7	Team 8	Team 9	Team 10	Team 11
1	Principal Investigator	5	x	x						x	x	x	
2	Principal Investigator	4				x			x	x			x
3	Operations Lead	4	x		x			x				x	
4	QI Lead	4	x				x	x			x		
5	Project Manager	3	x				x					x	
6	Project Coordinator	3	x					x		x			
7	Project Specialist	2							x				x
8	Project Manager	2		x						x			
9	Faculty Team Leader	2		x						x			
10	Research Coordinator	2							x	x			
11	Project Manager	1		x									
12	Project Coordinator	1				x							
13	Faculty Team Leader	1					x						
14	Operations Manager	1					x						
15	Content Manager	1					x						
16	Analyst	1					x						
17	Research Coordinator	1		x									
18	Project Coordinator	1			x								
19	Content Manager	1	x										
20	Project Coordinator	1					x						
	Total participants by team		6	5	2	2	7	3	3	6	2	3	2

Table 3: Individual study participants and their respective team affiliations

The sampling frame of potential participants consisted of all C3N Project collaborators who were officially employed by CCHMC during the 2012 – 2014 observation period, a fluctuating group of about fifty people at any given time based on C3N team rosters. We identified several potential biases based on study participants. Individuals who volunteered to participate might exhibit some level of systematic difference in collaboration styles or communication patterns that could potentially distort our network models.

C3N Project collaborators were based in different geographic regions (3.6 locations per team, on average) and affiliated with multiple institutions, but our study participants were all employees of CCHMC (across four locations). Central operations for the C3N Project occurred on site at CCHMC. Each team in our sample had one or more employees as core members, so heavy participation from CCHMC was essential for achieving representative network coverage via email data. But the lack of external collaborators as study participants presents a potential deficiency as well as the possibility that we missed some interesting variation in network dynamics occurring on the periphery, where innovative ideas often emerge (Provost and Jarvenpaa 2014; Rogers 2010).

C3N Project team members based at an organization other than CCHMC still appeared in the email communication networks. Collaborators appeared as actors in network models generated for this study if: (1) they were one of twenty official study participants contributing data directly from the email account, (2) they are a known team member appearing on monthly reports, and one or more of the following: (3) they sent an email message to a study participant (directly or in carbon copy), or (4) they received an email from a study participant (directly or in carbon copy), or (4) they received an email message from team member to which a study participant was carbon copied.

4.2.3 Sampling Approach and Team Selection

Survey-based social network analysis (and other methods for sociometric data collection based on recall and self-reports from network actors) conventionally demand high participant response rates because the “total universe” is needed (Tichy et al. 1979: 510). Digitally-driven SNA is advantageously robust to lower participant coverage. Analysis by Zilli and colleagues (2006) of email-based network modeling suggests that good approximations of group network structures may be generated using messages from as little as 25% - 30% of group members’ mailboxes. For the sake of validity, we wanted to observe team communication dynamics in uniformly representative team networks. Thus we used 25% (of team members sharing their mailboxes) as a threshold for including a team in our sample.

We used a population-based sample (Stuart 1962), including teams if at least 25% of core members were active participants in this study, i.e. sharing their email archives, and if the teams were active during our observation period. Eleven teams met these criteria. We also considered the extent to which these eleven teams were generally representative of a typical virtual innovation team in the modern digital workforce. Multiple facets of the eleven teams in our sample were generalizable in that sense. For one, virtual communication was the primary mode of interaction for these teams, notwithstanding the presence of colocated collaborators on each team. Each virtual team in this study also had at least two non-colocated members at an average 3.6 locations across teams.

Secondly, these teams are demonstrative of the increasing number of work groups embedded in collaborative innovation networks forming with and across industries and institutions during the past several decades (Benkler 2011; Gloor 2006; Yoo et al. 2012). Such teams are increasingly multidisciplinary and diverse with respect to expertise, status, and experience. The C3N Project evolved as a collaborative network of diverse contributors including clinicians and researchers as well as patients and their families.

Furthermore, the teams observed in this study were (and some still are) doing innovative work, designing and developing new products, services, and systems to be part of a radically improved system for chronic disease management. Innovation team targets included software design, mobile phone applications, programs for patient engagement, platforms for streamlining data collection, tools for knowledge collaboration, methods for connecting patients, and strategies for building awareness about pediatric chronic disease.

Finally, the eleven teams observed in this study are representative of teams in a canonical sense. C3N Project team members worked interdependently towards shared goals to produce something useful for themselves and/or their organization (Argote and McGrath 1993; Goodman et al. 1986).

4.2.4 Observation Period

Partitioning of time in this study was based on the periodicity of team outcome ratings. Our total observation period was twenty-three months with nine time periods (Table 4), four of which encompassed two months with the remaining five each encompassing three months. We used social network analysis (SNA) to generate observations of network structures and communication behaviors for each team during each time period.

	Time period start	Time period end	Duration (days)
1	September 1, 2012	November 30, 2012	90
2	December 1, 2012	February 28, 2013	89
3	March 1, 2013	May 31, 2013	91
4	June 1, 2013	July 31, 2013	60
5	August 1, 2013	October 31, 2013	91
6	November 1, 2013	January 31, 2014	91
7	February 1, 2014	March 31, 2014	58
8	April 1, 2014	May 31, 2014	60
9	June 1, 2014	July 31, 2014	60

Table 4: Time period intervals (n = 9) during 23-month observation period

4.2.5 Email Data Collection

Collection of email data from study participants occurred systematically via Internet Message Access Protocol (IMAP) accounts in the Microsoft Outlook email platform. IMAP usernames and passwords differed from participants' existing email credentials. This set-up avoided the need to share passwords and conformed to CCHMC email security requirements. Voluntary study participants *(n = 20)* installed Microsoft Outlook message rules to enable both sent and received messages to be copied to the IMAP account and to filter project-related emails without manual data cleaning. Rules were developed through iterative testing by this author and CCHMC research coordinators based on feedback from team members and systematic experimentation during and after each email data export. CCHMC research coordinators harvested messages bi-monthly. Three to five days prior to each email export, research coordinators emailed study participants to request that they check IMAP inboxes for functionality. This process allowed for manual removal by participants of personal, confidential, or irrelevant messages at their discretion. Comprehensive information on technical aspects of the email data collection process (displayed visually in Figure 1) may be found in Appendix A.

The following section will describe how the primary email data were organized to create team-specific network models consisting of email messages containing one or more innovation keywords sent or received during September 1, 2012 – July 31, 2014 by a known team member.

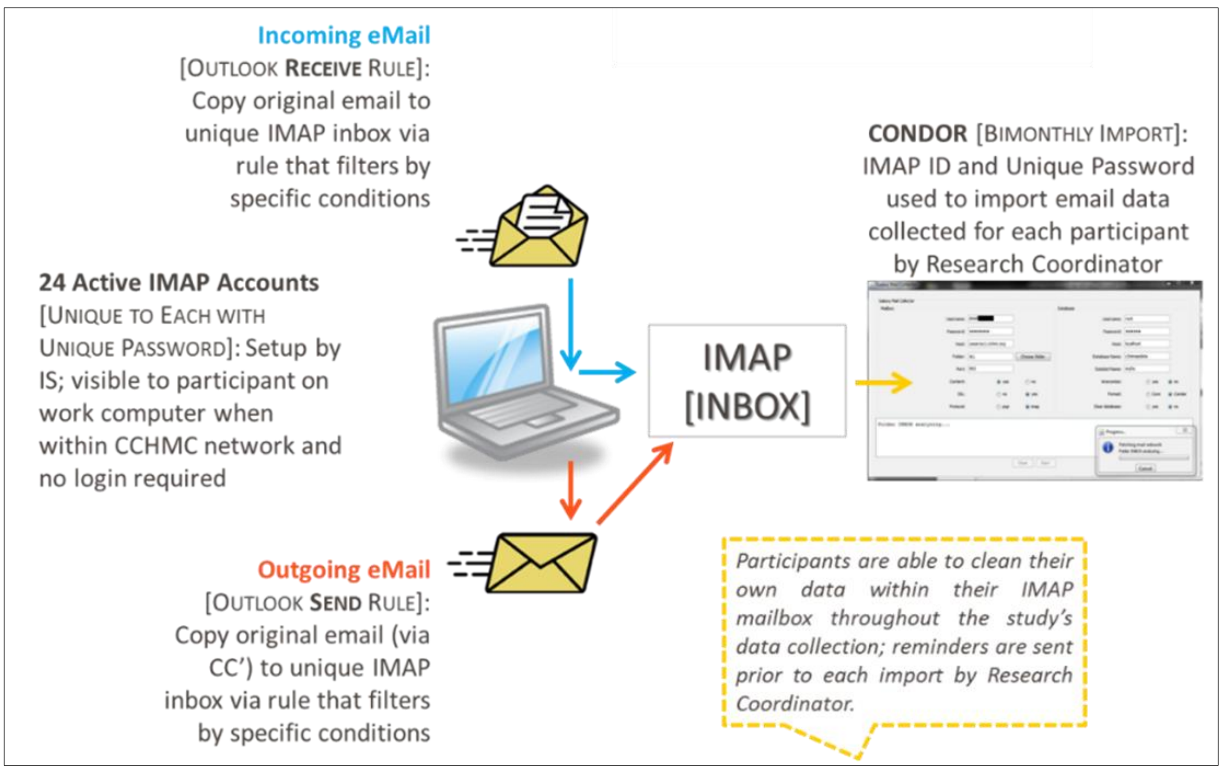


Figure 2: Email data collection technical processes

4.3 Social Network Analysis

4.3.1 Email Data Cleaning and Analysis

From each message harvested, we documented the sender, recipient or recipients (including carbon copies), time stamp, subject line, and message content. A raw dataset with 72,880 network actors and 3,471,011 email messages was imported into the Condor software platform (Gloor et al. 2004; galaxyadvisors.com). Condor is a network and semantic analytic software, a set of tools to translate digital observations into observations of network structures and communication behaviors. Condor generates network graphs, sociograms, adjacency matrices, and other graphics depicting the evolution of interactive communication flows (Gloor and Zhao 2004).

Recall from the previous chapter that social network analysis (SNA) is an established approach to study workplace interactions and detect behavioral signals (Wasserman and Faust 1994). Networks represent interaction structures among sets of interconnected units, such as members of a team, and may be represented visually or mathematically (Borgatti et al. 2009). We refer to the units as network actors or nodes and usually draw them as points. Connections (also known as links or edges) between nodes are drawn as lines and materialize in network models based on some property of interaction between two actors.

We created network graphs as visual representations of communication networks for each team in each of nine time periods over twenty-three months (September 2012 – July 2014). On our email network graphs (similar to the example shown in Figure 3), nodes represented individual team members and edges represented connections via exchange of one or more messages during the focal time period. The more messages exchanged, the closer the correspondents appeared on the network graph.

We used Condor software for social network analysis (SNA). SNA in this study consisted of generating visual network graphs and characterizing networks with respect to structure and dynamics across teams and over time. To capture network observations for Team 1 during Time 1, for example, we opened the Team 1 sub-dataset (the generation of which is described in the next section) in Condor and filtered by the dates associated with Time 1 (September 1, 2012 – November 30, 2012). Next, we used the Condor Annotate menu to calculate measures characterizing network structures and communication patterns. Appendix B outlines the precise steps and settings used in Condor to generate observations for our network-based predictor variables. Data were exported from Condor to a Microsoft Excel file for organization and analysis.

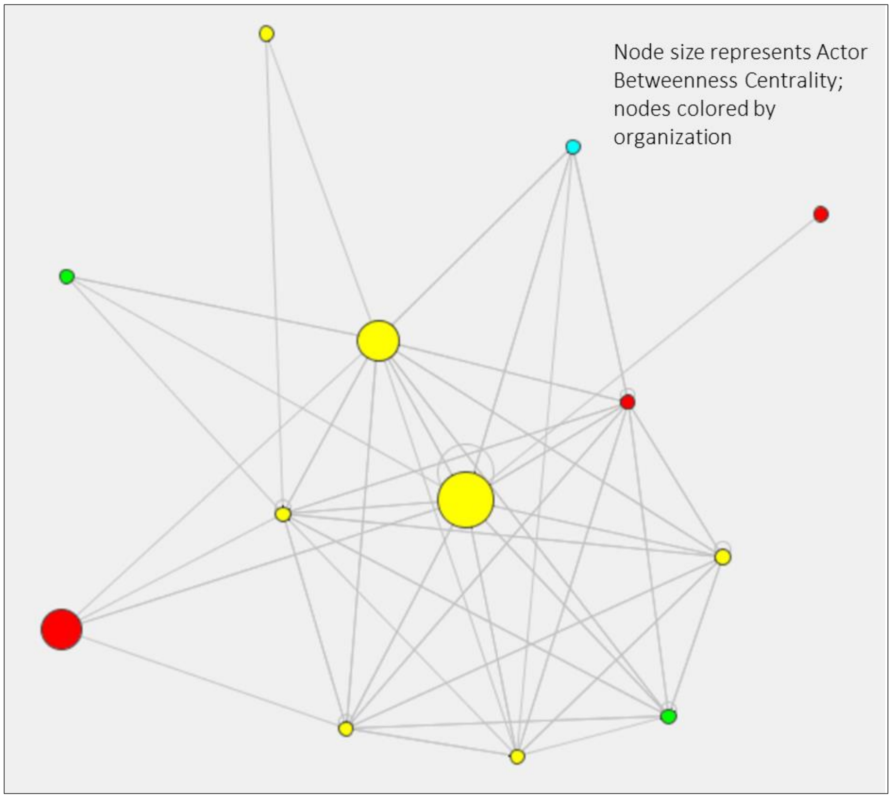


Figure 3: Network graph example for one team

4.3.2 Creating Team Network Models

We began analysis with an email archive data set containing 3,471,011 messages from January 1, 2011 – August 11, 2014. We used Condor to generate eleven sub-network datasets by filtering (Figure 3) with respect to senders and recipients (network actors), message content, and time. From the full dataset with 72,880 actors we searched for known team members identified by team rosters on monthly progress reports. We also sought feedback from project leaders with respect to team membership and the extent to which team members' participation was substantive. Known team members first names, last names, and email addresses were entered as queries in the Condor Actor Selection menu; resulting actors who matched team members were selected, merged, and grouped in a team-specific dataset.

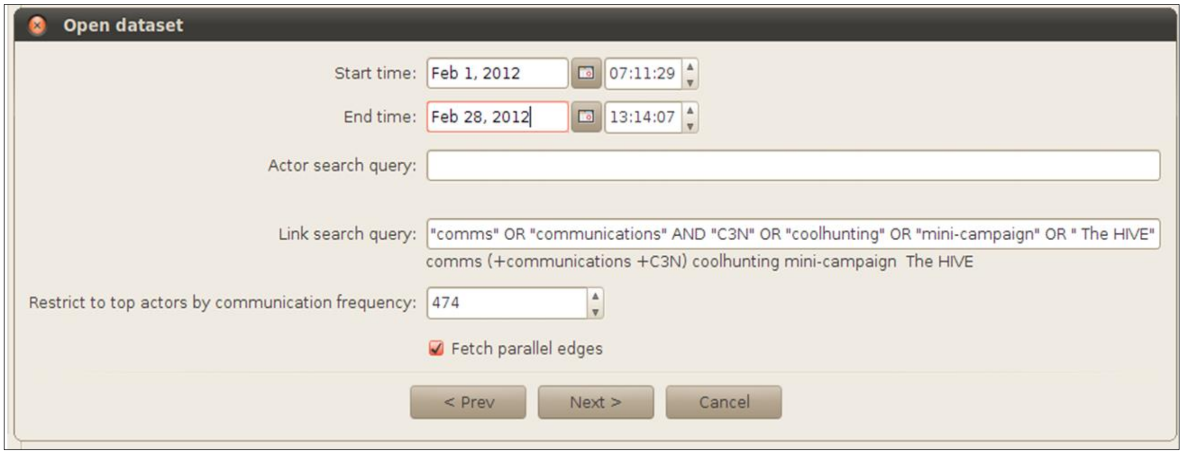


Figure 4: Filtering of email data with team-specific keywords

Many study participants contributed to more than one C3N Project team (as seen in Table 3) and most used their work email account for correspondence concerning other personal or professional commitments. Thus we needed a method to identify and separate messages associated with a particular innovation project for the purpose of using those messages to generate that project team's communication network model. We used keywords (Table 5) to filter messages from each of the team-specific sub-datasets.

C3N Team		Team-specific keywords for filtering messages from email archives
1	Communications	"comms" OR "communications" AND "C3N" OR "coolhunting" OR "mini-campaign" OR " The HIVE"
2	Enhanced Collaboration	"e3" AND "C3N" OR "patient status tracker" AND "C3N" OR "visit planner" AND "C3N" OR "enhanced collaboration" AND "C3N" OR "aim 2b" OR "aim2b"
3	EMMA App	"emma" AND "C3N" OR "game" AND "C3N" OR "ipads" OR "Impact III" OR "social games" OR "tung" OR "noel"
4	IBD Volunteers	"mentee" AND "C3N" OR "mentee" AND "IBD" OR "volunteers" AND "IBD" OR "narrative" AND "C3N" OR "story" AND "IBD"
5	ICN Exchange	"ICN exchange" OR "ImproveCareNow Exchange" OR "The Exchange" OR "P3K" OR "peer-produced practice knowledge" OR "pinboard" OR "metatags"
6	Patient Advisory Council	"patient advisory council" AND "C3N" OR "PAC" AND "C3N" OR "patient advisory council" AND "ICN" OR "patient advisory council" AND "ImproveCareNow" OR "patient scholars" OR "PAC chair" OR "PACers"
7	Passive PRO	"passive PRO" AND "C3N" OR "ppro" AND "C3N" OR "ginger.io" OR "electronic mobile sensing" AND "C3N"
8	Personalized Learning System	"n of 1" OR "n-of-1" OR "nof1" OR "personalized learning system" OR "myibd" OR "vital reactor" OR "orchestra" AND "C3N"
9	Population Management & Pre-Visit Planning	"population management" AND "ICN" OR "population management" AND "C3N" OR "pop management" OR "pop mgmt" OR "pre-visit planning" AND "C3N" OR "pre visit planning" "PVP" AND "C3N" OR "PVP" AND "ICN"
10	Clinical Team SNA	"Chicago" AND "SNA" OR "name generator" OR "Lyttle" OR "SNA Study" AND "C3N" OR "meltzer" OR "hougham"
11	YouMeIBD	"you me ibd" OR "youmeibd" OR "youapp" OR "you app" OR "YMIBD" OR "posegga" OR "roman" OR "baebler" OR "lauener" OR "jermain" OR "distler"

Table 5: Team-specific keywords for filtering email messages

We selected keywords based on suggestions from team members regarding terms relevant to their innovation and phrases that characterized their team vernacular. We validated keywords by confirming that known team members appeared among the most prominent and frequent communicators in network models generated by those keywords. Some keywords suggested by team members had to be discarded because they were frequently used terms (e.g., "platform") that, while perhaps relevant to a particular innovation project, failed to discriminate from messages containing "platform" that did not relate to the innovation project. Our selection of keywords also involved iterative sensitivity testing. During initial analysis for each team we added keywords one by one to the Condor query. This process increased our confidence that one particular keyword wasn't picking up a disproportionate number of irrelevant messages.

As described above, we used filtering and other features of the Condor platform to generate sub-datasets for each team in which actors were known team members and messages. So far in this chapter we have discussed research context, study participants, and data collection methods as well as the particulars of email data collection and how raw message data become network-based observations via analysis in Condor. The following section enumerates the variables used in this study.

4.4 Study Variables

4.4.1 Response Variables

Understanding the processes and outcomes of virtual innovation teams requires evaluation on multiple dimensions. We characterized outcomes for each team with ratings from project senior leaders with respect to work group performance and radical innovation.

Rating questionnaires were completed by hand on paper by two senior leaders (C3N Project Principal Investigators) during November 2012, February 2012, May 2013, July 2013, October 2013, January 2014, March 2014, May 2014, and August 2014 - nine sets of ratings in total. After each leader completed the survey individually, they met to discuss and agree on a consensus rating for overall team performance. At times, one leader deferred to the other's rating completely if he lacked insight about recent activities of a particular team.

4.4.1.1 Performance Variable

Work Group Performance was measured with a five-point rating on seven dimensions (Cummings 2004; Cummings & Cross 2003). Project leaders rated teams as (1 = "poor", 2 = "needs improvement", 3 = "acceptable", 4 = "exceeds expectations", 5 = "outstanding", or 6 = "not applicable") on the following dimensions: (i), Teamwork; (ii) Clearly defined problem selection; (iii) Appropriateness of methods used to solve problems; (iv) Innovativeness of solutions, (v) Quality of impact from results; (vi) Institutionalization of solutions; (vii) Clarity of presentation. We used a consensus-style rating based on discussion between the two senior leaders and did not examine the variation in each dimension across raters. We calculated a team score for performance during each time period by summing the consensus ratings for each dimension. Following validation procedures used in a previous study featuring this performance measure (Cummings & Cross 2003), we observed that the two leaders were able to reliably rate teams' overall performance across all seven dimensions ($\alpha =$0.87).

4.4.1.2 Innovation Variable

We measured *Radical Innovation* (Miron-Spektor et al. 2011) by asking project leaders to divide 100 points among four ordinal levels, allocating the most points to the levels that best described goals and activities of the focal innovation team. Assignment scales using point allocation to different characteristics or processes based on their relative ascendancy can help to neutralize the effects of social desirability bias (Arnold and Feldman 1981; Ravlin and Meglino 1987) in performance ratings. This approach was adapted from the Bonen scale (Darel et al. 1993) and inspired by other scales for radical innovation (Dewar and Dutton 1986; Gatignon et al. 2002; Subramaniam and Youndt 2005). We calculated a team score for radical innovation by setting weights (Level 1 "Duplicating existing products or processes" = 1; Level 2 "Improving and incrementally modifying..." = 2; Level 3 "Introducing...in use elsewhere" = 3, and Level 4 "Developing something completely new" = 4) and summing the weighted scores for each level (Bobko et al. 2007; Miron-Spektor et al. 2011a).

4.4.2 Innovation Process Phase Variable

To support innovation teams, the C3N Project promoted an "idealized design process" framework for structured innovation in four phases: design, prototype, pilot, and implement. We operationalized *Innovation Process Phase* with archival data from team monthly reports including a score from a forty-point innovation process checklist (Figure 5) spanning four phases. Team leaders checked off milestones to calculate team scores each month and submitted to the C3N Project Management Office for oversight. We used this progress scale to identify the appropriate innovation phase (design, prototype, pilot, or implement) corresponding in time with observations of team networks for testing of our hypotheses ("b") about the moderating effects of innovation process phases.

The extent to which relationships between our network-based variables and team outcomes vary across innovation phases is a key element of the theorization in this study. Thus we will provide some background on the innovation process checklist and phases as they were presented to the C3N innovation teams. Rooted in the philosophy of that "every system is perfectly designed to get exactly the results that it gets", the innovation phase framework builds on an "idealized design process" (Moen 2002). The process is characterized by four localized phases with names synonymous to their focal activities: design, prototype, pilot, and implement.

The instrument used by C3N Project teams to track their innovation processes was a forty-point scale in four phases; each phase encompassed with a checklist of ten milestones. The scale was designed to accommodate iterative testing, reverse sequencing, and the non-linear nature of new product development (Provost et al. 2013). A team's score within each phase is determined by the count of markers and milestones, but the scale does not specify a sequential order in which the milestones must be completed. Teams were encouraged to skip, repeat, and approach steps in ways that made sense for their team and the status of their focal innovation. For example, a team score could decrease if an idea was scrapped and the team returned to an earlier testing or design phase. This directional flexibility was intended to encourage teams to explore diverse ideas, learn from what doesn't work, and adjust accordingly to move forward with a fresh approach (McGrath 2011). Skipping phases is also an option; for example, not all teams need to prototype if they can test changes safely and feasibly in an existing system (Langley et al. 2009).

4.4.2.1 Design Phase

The purpose of the *Design* phase is to generate new ideas for changes that will better meet the needs of product or system users. Other activities include defining components of the proposed innovation (as well as their interdependencies), exploring relevant theories, and qualitative testing such as focus groups or case studies (Campbell et al. 2000). Ideas develop through screening and small scale tests that lead to more concrete concept designs and the crystallization of design targets (Fore et al. 2013).

Generating ideas, defining concepts, and specifying innovations		
Design	**Team recruited and roles defined; project charter completed**	☑
	Environmental scan and/or literature review	☑
	Define components of innovation and mechanisms to influence outcomes (e.g. begin driver diagram)	☑
	Complete workplan (e.g. specify timeline, deliverables, resources required)	☑
	Qualitative testing: interviews, focus groups, surveys, case studies	☑
	Screen and synthesize ideas and concepts; **identify potential barriers** to change surrounding innovation	☑
	Articulate theory for innovation (e.g. complete DD or conceptual model)	☑
	Develop plan for testing innovation (e.g. complete PEF) and **engage with IRB team** to complete IRB application	☑
	Execute sequential testing (e.g. PDSA) of innovation and concept designs; **solicit end user feedback**	☑
	Gate 1: Formal evaluation of concept design at SISC (with preliminary validation at SMC)	☑
		10

Figure 5: Innovation Process Scale – Design Phase

4.4.2.2 Prototype Phase

The *Prototype* phase is concerned with learning and expanding on concept designs. Prototypes are simulations, models, instantiations, enactments, and other artificial methods that demonstrate if/how an innovation will work. Prototypes are essential when a disruption to the status quo is desired and the new system does not yet exist (Langley et al. 2009). Work in the prototyping phase serves to test that the desired performance and results are built into the design, detect likely problems, and evaluate resources needed for further testing in an existing targeted system (Moen 2002).

	Testing of innovation in artificial environment	
Prototype	**Prototype needed?** If no, proceed to formal evaluation for pilot testing If yes, define team and update charter	☑
	Complete prototype workplan (e.g. specify timeline, deliverables, resources)	☑
	Share learning from design phase and/or prototype development (e.g. present at SITM or SRC)	☑
	Build on conceptual designs with **content and execution theories** (e.g. update DD)	☑
	Execute sequential (PDSA) **cycles of testing and learning** around feasibillty of the innovation	☑
	Solicit feedback from internal customers and end users (e.g. PAC and/or ICN and/or crowdsourcing)	☐
	Troubleshoot problems; explore learning curve (e.g. assess needs for training / education around innovation)	☑
	Establish standard processes & procedures around prototype (e.g. complete MOP(s))	☐
	Plan for further testing / resources; identify pilot testers(e.g. update PEF / IRB amendment)	☐
	Gate 2: Formal evaluation of prototype at SISC (with preliminary validation at SMC)	☐
		6

Figure 6: Innovation Process Scale – Prototype Phase

4.4.2.3 Pilot Phase

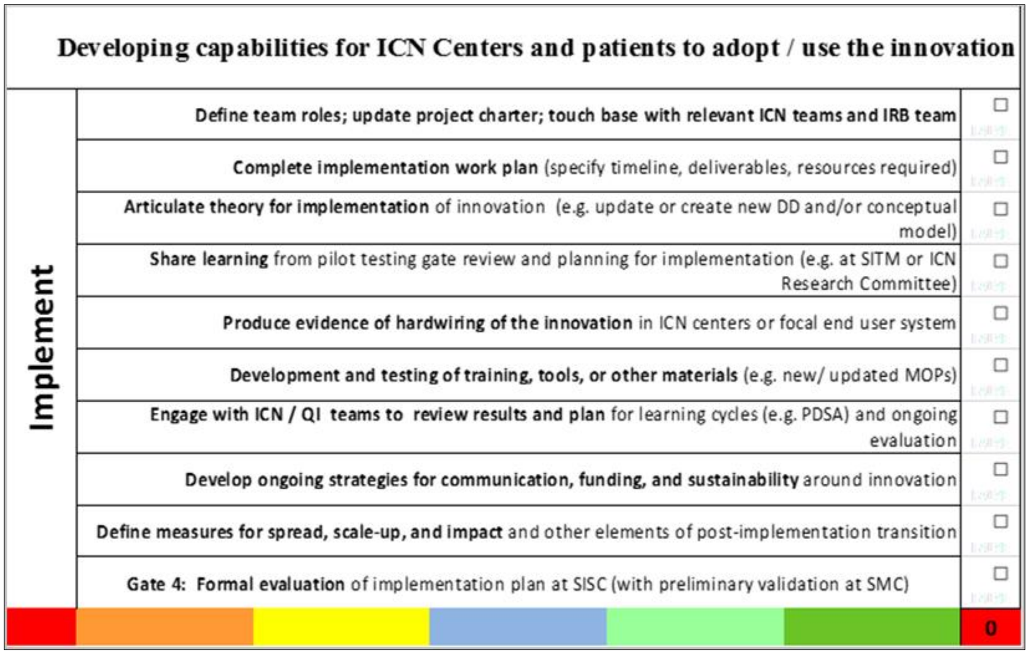
Pilot phase testing involves iterative cycles of testing and learning in the focal system targeted for re-design (Parry et al. 2013). Methods for testing and implementing are also expanded on in the social construction of the new product or practice. The design science literature supports the iterative aspect of pilot testing and "emphasizes the interdependence of building, intervention, and evaluation" (Sein et al. 2011: 53). Innovations will likely need refinement to overcome institutional inertia and support for the status quo (Langley et al. 2009).

Testing of innovation with selected ICN centers or controlled group of end users		
Pilot	**Define team roles; identity pilot testers; update project charter; touch base with IRB team**	☐
	Complete pilot workplan (e.g. specify timeline, deliverables, resources required)	☐
	Engage with other teams and/or project leadership to discuss learning from prototype testing (e.g. share at SITM or SRC)	☐
	Execute sequential cycles of testing and learning (e.g. PDSA) around piloted innovation	☐
	Solicit feedback from internal customers (e.g. PAC, ICN) and/or other end users of innovation	☐
	Formal analysis of pilot data / results; assess process/outcome measures (e.g. update PEF as needed)	☐
	Develop/ test programs for **end user orientation** and **communication strategies** (e.g. update MOPs)	☐
	Assess resources required and capacity of innovation users to support further testing or implementation	☐
	Develop and document plan for implementation (e.g. update PEF; engage with ICN and other C3N teams)	☐
	Gate 3: Formal evaluation of pilot at SISC (with preliminary validation at SMC)	☐
		0

Figure 7: Innovation Process Scale – Pilot Phase

4.4.2.4 Implementation Phase

Important factors for learning in the *Implement* phase include rates of uptake and impact and the stability of the innovation as it is adopted by an increasing number of system users (Campbell et al. 2000). More learning cycles with ongoing evaluation are required as the innovation becomes increasingly embedded across a wider range of contexts and institutional changes are made to accommodate new processes and products (Berwick 2003; Hargadon and Douglas 2001; Lanham et al. 2013).



Developing capabilities for ICN Centers and patients to adopt / use the innovation		
Implement	**Define team roles; update project charter; touch base with relevant ICN teams and IRB team**	☐
	Complete implementation work plan (specify timeline, deliverables, resources required)	☐
	Articulate theory for implementation of innovation (e.g. update or create new DD and/or conceptual model)	☐
	Share learning from pilot testing gate review and planning for implementation (e.g. at SITM or ICN Research Committee)	☐
	Produce evidence of hardwiring of the innovation in ICN centers or focal end user system	☐
	Development and testing of training, tools, or other materials (e.g. new/ updated MOPs)	☐
	Engage with ICN / QI teams to review results and plan for learning cycles (e.g. PDSA) and ongoing evaluation	☐
	Develop ongoing strategies for communication, funding, and sustainability around innovation	☐
	Define measures for spread, scale-up, and impact and other elements of post-implementation transition	☐
	Gate 4: Formal evaluation of implementation plan at SISC (with preliminary validation at SMC)	☐
		0

Figure 8: Innovation Process Scale – Implementation Phase

4.4.3 Predictor Variables

Recall from the previous Theory Development chapter that network structures can represent underlying social dynamics and are thus influential in shaping team processes and performance (Cummings and Cross 2003; Phelps et al. 2012; Sparrowe et al. 2001).

4.4.3.1 Team Centrality Variable

Network models use structural concepts to describe how information and resources are distributed in groups (Burt et al. 2013). *Team Centrality* refers the extent to which one or a few individuals dominate interactions by connecting other individuals who are not otherwise linked or perhaps weakly connected (Freeman 1977). High team centrality would suggest a single individual controlling most communication flows while low team centrality indicates direct connections between all participants without intermediaries. Following previous organizational research associated with the flow of information in networks (Brass and Burkhardt 1993; Cross and Cummings 2004; Flynn and Wiltermuth 2010; Hansen 2002; Shaw et al. 2005), we adopted betweenness centrality as a measure of team centrality.

Group Betweenness Centrality (GBC) (Freeman 1977, 1979) was used to operationalize Team Centrality. GBC is a group-level measure based on the extent to which *actor betweenness centrality*, an individual-level measure, varies across actors in the network. The actor betweenness centrality of network node (v) is given by:

$$C_B = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where σ_{st} is the number of shortest paths from node *s* to node *t* and $\sigma_{st}(v)$ is the number of those *s*-to-*t* paths that pass through node (v) (Wasserman and Faust 1994). Actor Betweenness Centrality captures the extent to which an individual lies 'between' others in the network (Borgatti and Everett 2006). Individuals with high actor betweenness centrality have been associated with advantage, status, and leadership (Borgatti and Everett 2006; Padgett and Ansell 1993).

GBC, calculated as the fraction of shortest paths between all pairs of nodes that pass through at least one node in the group (Wasserman and Faust 1994), is given by:

$$\frac{\sum_{i=0}^{g}[C_B'(n^*) - C_B'(n_i)]}{[(g-1)^2(g-2)]/2}$$

where g represents the total number of network nodes and C_B' represents the value of betweenness centrality for a particular actor. The numerator of the GBC equation above sums the differences in betweenness centrality for the actor with the highest centrality $C'_B(n^*)$ and each of the other i actors $C'_B(n_i)$. The demoninator represents the theoretical maximum value of betweenness centralities for all g nodes in a network (Adamic 2015).

GBC ranges from zero to one. Lower values indicate democratic group structures in which communication patterns are comparable for each node and higher values represent star-like structures with one or a few central nodes (Figure 9) (Borgatti 2006). Examples of high and low GBC are displayed in Figure 10 as seen on network graphs for one team in this study.

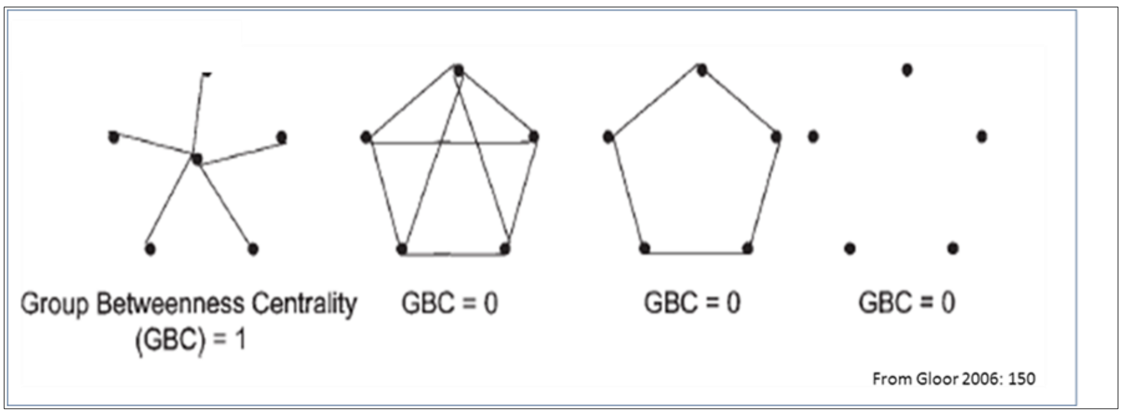
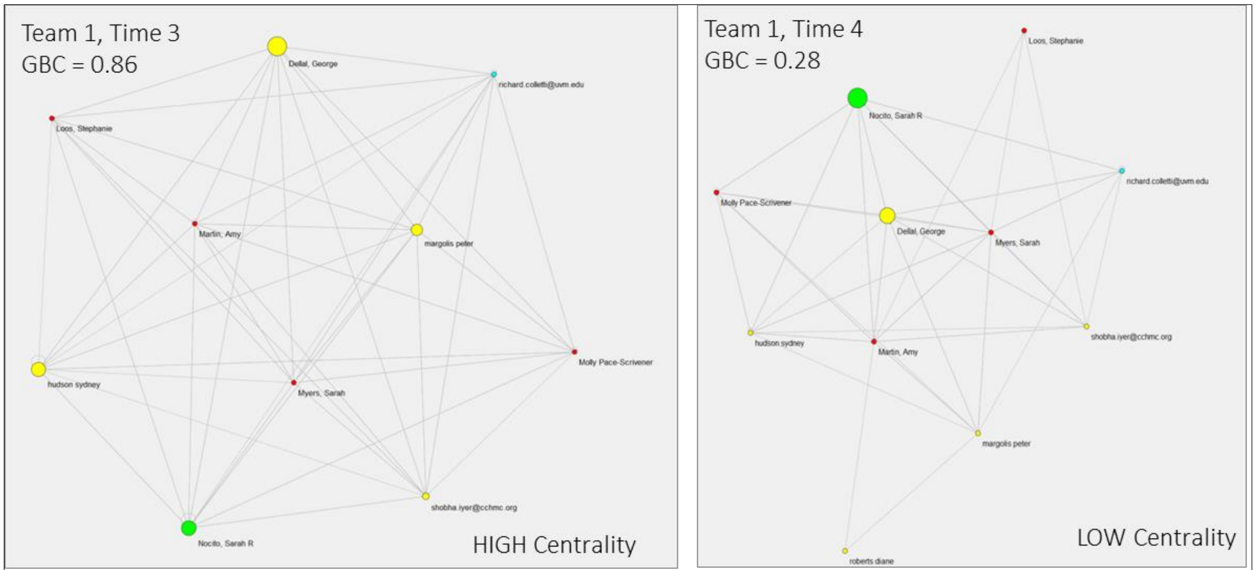


Figure 9: Group Betweenness Centrality



Node size represents Actor Betweenness Centrality; nodes colored by organization

Figure 10: Examples of high and low Group Betweenness Centrality

4.4.3.2 Structural Dynamics Variables

Our theorization around virtual innovation teams also concerns *Structural Dynamics*, referring in this study to the extent of change in levels of team centrality over time. We propose that changes in the level of GBC over time represent changes in the ways that teams are collaborating, perhaps in response to shifting resources or demands of the innovation process.

Structural dynamics was operationalized as the *average of squared weekly changes in team centrality*. To quantify structural dynamics with respect to team centrality, we calculated the squared distance between each weekly observation in team trajectories of GBC plotted over time. Then we recorded the average of those squared distances in each week w: $\frac{\sum_{i=1}^{W}(GBC_w - GBC_{w-1})^2}{weeks_i}$

Figure 11 displays GBC plotted over time for one team; the dotted lines represent differences between a weekly observation of GBC and the observation in the previous week. Each passing week will see a decline, no change, or an increase in the measure. We squared these distances between observations of GBC to account for negative values that occur when GBC drops from one week to the next, and calculated the average of the squared distances during the focal time period.

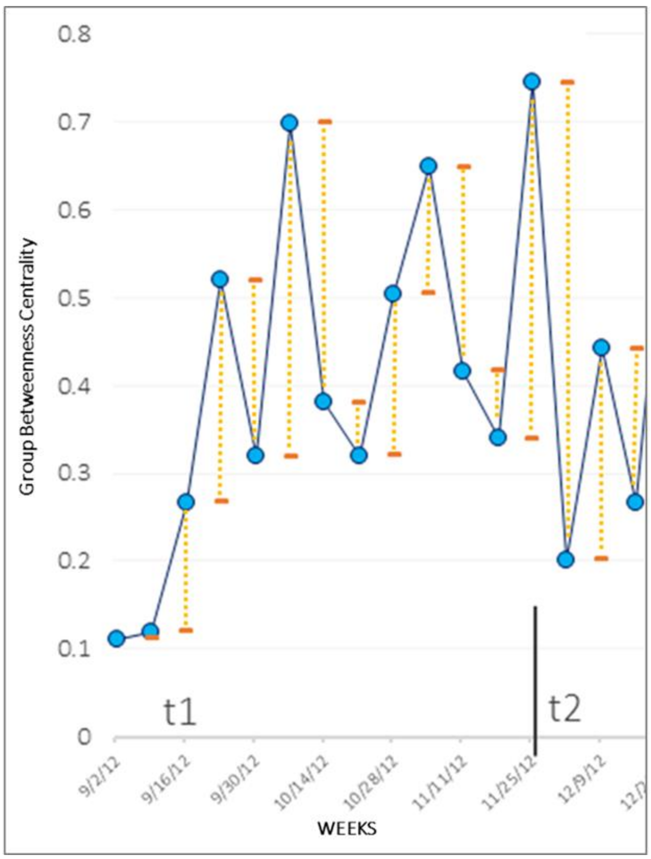


Figure 11: Measuring structural dynamics

Our development of this measure for team structural dynamics follows previous studies (Gloor et al. 2007; Kidane and Gloor 2007) drawing on the *count* of oscillations in centrality as an indicator of structural dynamism in communication networks. The count of oscillations is calculated as the sum of local maxima and minima (i.e., directional changes) in the trajectory of the centrality measure plotted as a time series. Oscillation counts have predicted creativity and performance outcomes in multiple work contexts (Gloor et al. 2014; Kidane and Gloor 2007; Zhang et al. 2013). A team study of peer-to-peer communication patterns found low oscillations (i.e., few changes in centrality) to be associated with effectiveness and execution, whereas the more creative teams exhibited high oscillations (Gloor et al. 2007).

Building on the measure of oscillation counts, this research considered the *magnitude* of changes in team centrality. Counting oscillations can detect the occurrence of change in team centrality levels, but tells us nothing about the extent to which those changes are slight or extreme. It is feasible that a team could have a high count of oscillations without much change in the overall level of centrality. Similarly, team centrality levels might shift infrequently but also represent drastic differences when change does occur. Thus we have used the squared distances between observations of team centrality as a measure of the extent of change in team centrality over time.

4.4.3.3 Participation Equality Variable

Participation Equality is a construct originating from theorization about virtual collaboration and computer-mediated communication (Burke and Chidambaram 1995; Desanctis and Gallupe 1987; Weisband et al. 1993). Equality of participation has been examined as a factor in research on team performance and decision making (De Dreu and West 2001; Locke et al. 1997; Mesmer-Magnus and DeChurch 2009; Stasser and Titus 1985). Operationalization of this construct has varied to the extent that a distinction is warranted between observed participation equality and participation equality as it is perceived by group members (Zmud et al. 2001). Perceptions of participation equality have been measured via self-reported evaluations in a laboratory experiment (Jarvenpaa et al. 1988) and with surveys (Berdahl and Craig 1995; De Dreu and West 2001). Observed participation equality is a quantitative summary of how participation inputs are distributed in a group (Zmud et al. 2001). The most common measure of participation equality involves the standard deviation of team members' comments or words counted within a particular time frame (Paletz and Schunn 2011). Other studies use the coefficient of variation as a relative standard deviation of individual participation rates (Siegel et al. 1986).

We conceptualize equality of participation on a virtual innovation team to entail evenly distributed task activities and comparable levels of initiative amongst team members as evidenced by balanced communication behaviors. Following studies that used variability in group members' participation to characterize participation as distributed at the team level, we operationalize Participation Equality as a function of variation in team members' communication activities and communication frequency. The measure is called *Average Weighted Variance in Contribution Index* (AWVCI) and was developed through research based on digital social network analysis (Gloor et al. 2008).

Contribution Index (CI)**,** an individual-level measure of participation in group email correspondence, is the basis for calculating AWVCI at the group level. Individual contribution indices quantify the extent to which communication is balanced with respect to sending and receiving messages, calculated as (Gloor et al. 2003):

$$\frac{\textit{Sent messages} - \textit{Received messages}}{\textit{Total messages sent and received}}$$

Figure 12 displays individual CI plotted on the vertical axis against communication frequency (total number of messages sent or received) on the horizontal axis, identifying typical communication patterns for various collaborative roles.

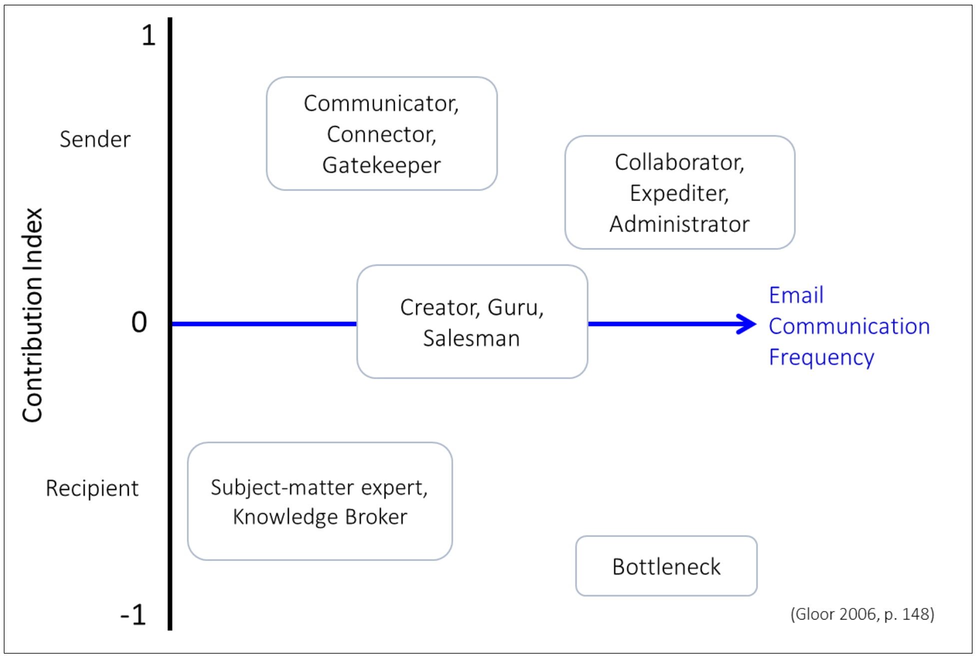


Figure 12: Communication Index plotted by communication frequency

The Contribution Index measure ranges from -1 to 1. If an individual only sends messages, their index is 1; if only a recipient, their index is -1. Values below zero indicate that an individual receives more messages than he or she sends; values above zero signify more sending than receiving.

Most previous measures of participation equality build on the overall frequency of contributions, but we also consider whether communication activities are outgoing or incoming in the form of email messages sent and received. Anticipation Ratio is another measure associated with team performance that incorporates the directionality of communication, calculated as the ratio of the number of communications transferring information to the number of communications requesting information (Entin and Serfaty 1999). Values of the anticipation ratio greater than one indicate efficiency of communication in the sense that team members pushed information more than it was pulled, anticipating each other's needs (Macmillan et al. 2004).

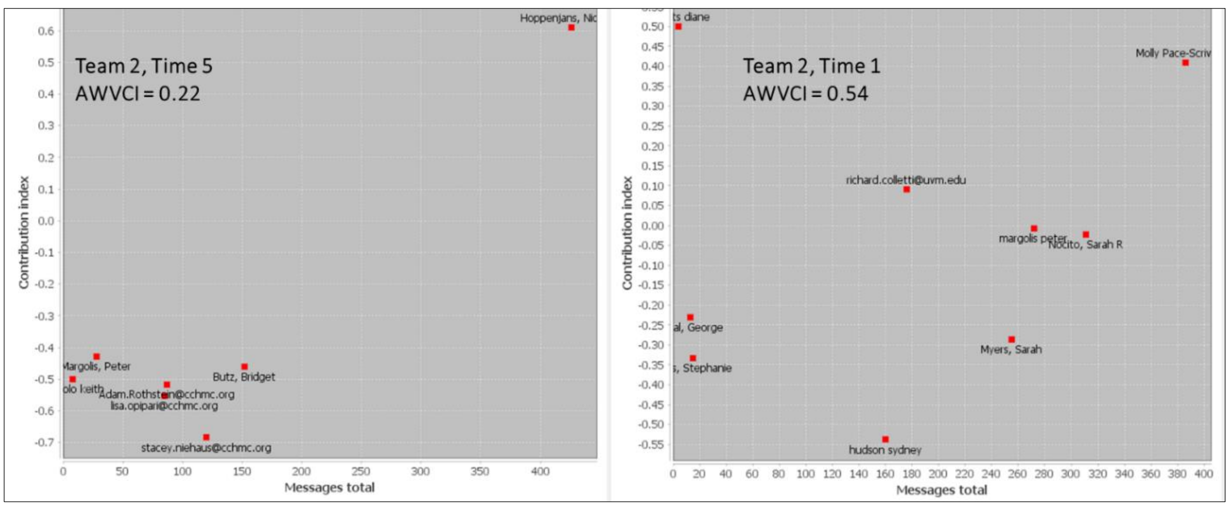


Figure 13: Examples of high and low Average Weighted Variance in Contribution Index

Low levels of variance in individual contribution indices suggests that group members have comparable frequency of communication and that one or a few individuals are not doing a disproportionate amount of either sending or receiving messages (Gloor et al. 2008). Examples of low and high AWVCI observations for one team are displayed in Figure 13.

The 'weighted' element of AWVCI is the total number of messages (below, m_i) exchanged during day *i* of the focal time frame. This weighting serves to reduce the distortion in variance caused by single messages from one actor during low-activity periods and to increase the influence of messaging that occurs during high-activity periods (Camarinha-Matos et al. 2006). AWVCI is calculated by:

$$\frac{\sum_{i=1}^{T} m_i \cdot var(c_i^{ws})}{\sum_{i=1}^{T} m_i}$$

where m_i represents the total messages exchanged on day *i*, *ws* represents "window size" or the number of days in which contribution indices c_i are observed. Finally, c_i^{ws} in the numerator above represents a vector of contribution indices for each group member on day *i*.

In this section we have outlined two response variables (performance and innovation) and three network-based explanatory variables (GBC, average of squared weekly changes in GBC, and AWVCI. The following section will describe the background variables used in this study, for the purpose of ruling out some plausible alternative theories for the variation we observed in virtual innovation team outcomes.

4.4.4 Background Variables

Previous studies of innovation teams indicate that performance may be affected by variation with respect to resources, processes, tasks, and the working environment (Hülsheger et al. 2009). Drawing on team research (Cohen & Bailey 1997; Kozlowski & Bell 2003) and recent studies of virtual teams (Martins et al. 2004; Gilson et al. 2014), we considered a range of background variables and the extent to which these factors might explain or modify associations between team outcomes and our network-based predictors. Background variables were selected with the aim of gaining insight about unexplained variation in team outcomes and ruling out alternative theoretical explanations.

We prioritized team diversity factors over team mean levels during background variable selection, an appropriate action given that emergence is a central theory foundation of this study. Following previous studies incorporating group diversity, we selected the coefficient of variation – the standard deviation of group member observations divided by the group mean – as a measure of dispersion describing the amount of variability relative to the mean level (Allison 1978). Team size and other inputs varied across the lifespan of C3N innovation projects, so we considered team composition and other variables to be dynamic and calculated observations of background variables during each of the nine time periods.

4.4.4.1 Network Actors

We represented team size as the number of team members appearing in the email network during a focal time period. We wanted to detect active participation and the email network seemed to be a more honest source than were the member rosters from team reports. Team size is a classic input variable that may have distinctive influence on virtual team performance as compared to colocated teams (Martins et al. 2004).

4.4.4.2 Network Density

The ratio of active network connections to the total number of potential connections between actors has been used in social network research as a measure of average levels of communication (Leenders et al. 2003) and overall relational strength (Reagans & Zuckerman 2001).

4.4.4.3 Project Duration

This variable capturing the length of the innovation project lifespan was measured as the number of months since team inception.

4.4.4.4 Team Member Locations

Time and space are key variables of virtual team interactions. We controlled for geographic dispersion with by counting the number of team member locations and dividing by the number of team members. We considered team members to be in separate locations if they did not work in the same building.

4.4.4.5 Team Member Tenure Diversity

We measured individual team member tenure as the number of months since a team member appeared on a team roster or as an actor in the email communication network. Tenure diversity was operationalized as the coefficient of variation for team members' individual tenure.

4.4.4.6 Status Equality

We controlled for the extent to which status positions of team members are dispersed (Christie and Barling 2010; Freese 1974). Some studies indicate that status effects are diminished in virtual interactions (Sproull & Kiesler 1986); other evidence suggests that hierarchies persist (Cramton 2001). Status and boundaries have traditionally been pronounced in health care organizations (Tucker 2003). We calculated the coefficient of variation for individual team member status, ranked on an ordinal scale of low (1), medium (2), or high (3) status and based on professional and educational history and team role.

4.4.4.7 Gender Distribution

The proportion of females in a group may be an important determinant of collective intelligence and performance (Woolley et al. 2010). We counted the number of female actors appearing in the email network during a focal time period divided by the total number of actors.

4.4.4.8 Additional Background Variables Considered

We investigated several other background variables that were not ultimately included in our statistical models for hypothesis testing. We measured frequency of communication (Cummings & Cross 2003) with the number of *network connections* linking network actors. In our email network models, a connection between sender and recipient(s) occurred every time a message was exchanged, so it is a good indicator of the frequency of online communication for the team. Another dimension of team virtualness considered was the extent to which team members are clustered by location in subgroups (Jarman 2005; O'Leary & Mortensen 2010). *Colocation* may be a driver of project team performance in some capacity (Zenun et al. 2007). This measure was calculated as the maximum number of colocated members divided by the total number of team members. We assessed *team affiliations diversity* to capture variation in multiple team membership (Espinoza et al. 2003; Cummings & Haas 2012), or the extent to which team members were also involved in other C3N Project innovation teams.

Thus far we have introduced the research context, data sources, methods, and measurement. The chapter concludes with summary of data analyses for both discovery and estimation.

4.5 Analysis

We conducted our analyses in several steps: (1) descriptive and graphical, to enhance understanding of our observations, (2) investigative, to inform model selection, and (3) evaluative, estimation procedures. We tested our six hypotheses with a series of linear models for panel data.

4.5.1 Graphical Analysis

We first wanted to describe and visualize our network models as well as the trajectories of measures used to characterize team networks. This approach is suggested by Snijders (2005: 4): "any empirical analysis of longitudinal network data should start by making a basic data description in the form of making graphs of the networks or plotting some basic network statistics over time." We generated network graphs (similar to Figure 3) and contribution index plots (similar to Figure 13) for each team during each time period to visualize the development of team communication networks. For each variable, we also generated graphics that included histograms, box plots, scatterplots, time series charts, and Shewhart charts. These graphics served as a helpful check on quantitative summaries of the network model. Appendix C outlines our approach to checking the validity of our network-based measures.

4.5.2 Analytic Framework

This dissertation study draws on observations of the email communication networks of eleven teams in nine time periods over twenty-three months. Longitudinal or cross-sectional time series data are observations of multiple entities across time (Wooldridge 2010). We conceptualized our network-based observations as **panel data**, a common analytic framework for longitudinal data with multilevel structure (Baltagi 2008). Multiple prominent network-based studies in the management and organizational literatures have used cross-sectional time series methods, another term for the panel data framework (Lee et al. 2014; McFadyen et al. 2009; Reagans and Zuckerman 2001; Tortoriello et al. 2012).

Advantages of multilevel structure (if the data are in fact clustered) include unbiased estimators for coefficients and standard errors and also the opportunity to model faithfully the underlying reality of covariance structure (Gelman and Hill 2007). If a multilevel modeling structure is appropriate, primary options for panel data are Fixed Effects (FE) or Random Effects (RE) models (Snijders 2011). FE and RE account for unobserved heterogeneity across entities in different ways while OLS pooling ignores that heterogeneity (Bartels 2008).

There are many and sometimes conflicting guidelines in the literature with respect to selecting FE or RE (Searle et al. 1992). A FE model examines the extent to which group intercepts differ, assuming constant slopes and variation across groups (Gujarati 1995). A RE model for panel data assumes that unobserved heterogeneity across groups is not correlated with model predictors; the effects themselves are group-specific variance components (Park 2011). RE models are indicated if omitted variables may be constant over time but varying across observed units. RE models were appropriate for this study because it is reasonable to assume that unobserved differences across time may influence our response variables (Dougherty 2007). Additionally, RE will afford modeling of both within- and between-team variation with the option to include time-invariant characteristics (Kohler and Kreuter 2005). Finally, RE allow for generalization of inferences from results beyond the sample used in the model (Torres-Reyna 2007).

RE are an efficient choice for analysis of unbalanced panels because information is not added linearly with additional observations from the same entity. RE models are more accommodating of covariance structures that often emerge in panel data, such as autocorrelation, heteroskedasticity, and cross-sectional dependence. Indeed, panel data – successive observations in time spanning multiple entities - are inclined to violate assumptions of independence and consistent variance (Hoechle 2007). Model error may be clustered by group or patterned over time or both (Torres-Reyna 2007). Below we outline exploratory analyses used to gain understanding of our multilevel data structure and thus inform estimation model selection.

4.5.3 Preliminary and Diagnostic Analysis

This section will summarize our analyses of error structure and testing procedures to explore optimal modeling choices for our panel data set. Information on specific tests and procedures used during data discovery are listed in Table 6.

Modeling Concerns	Test or Procedure	Null Hypothesis	Conclusion	STATA Routine	Reference	Remedy or action
Indepen-dence	Panel data autocorr-elation Durbin-Watson Test	Model errors over time are independent	Reject: First order autocorr-elation AR(1)	lmadwxt	Shehata & Mickaiel 2015a	Linear models with AR(1)
Heteroske-dasticity	Wald test for groupwise heteroske-dasticity	Variance of the error terms is consistent	Reject: presence of heteroske-dasticity	xttest3	Baum 2001	Robust standard errors of various stripes
Pooled or panel?	Breusch-Pagan Lagrange multiplier	Team-level variance components jointly equal zero	Reject: use Random Effects; FTR: use OLS	xttest0	Breusch & Pagan 1980	Use simplest model that best captures underlying reality of error structure; try many models
Fixed or Random effects?	Test of over-identifying restrictions Sargan-Hansen (χ^2)	No correlation between model predictors and errors	Reject: Fixed Effects; FTR: Random Effects	xtoverid	Schaffer & Stillman 2015	
Cross-sectional dependence	Pesaran test for cross-sectional dependence	Independence of errors across panel entities	Reject: Cross-sectional dependence	xtcsdc	Pesaran 2004	Panel-corrected standard errors
Linearity	Ramsey's Regression Equation Specification Error Test (RESET)	Panel Model is specified (no omitted variables)	Reject: panel model is mis-specified	resetxt	Shehata & Mickaiel 2015b	Transformation or addition of a polynomial predictor

Table 6: Diagnostic procedures for linear panel models

Any analysis based on linear regression should involve a check of model assumptions (linearity, homoskedasticity, independence, and normality) using residual model errors. Panel data model errors also merit special consideration. Panel data may be clustered over time. First order autocorrelation, abbreviated henceforth as AR(1), indicates the presence of correlation between time-adjacent observations (Baltagi and Wu 1999). In other words, AR(1) means that errors made by our model today are related to those made yesterday, a violation of the independence assumption for linear regression. Data with multilevel structure may have model errors with inconsistent levels of variance across entities, violating the assumption of homoskedasticity.

We weighed the benefits of a team-level modeling structure (over pooled OLS). If a response variable varies across groups such that predictor variables are not sufficiently explanatory, fitting a pooled model that does not account for group-level structure can produce biased and inefficient estimates (Beck and Katz 1995). Given that a multilevel modeling structure is appropriate, primary options for panel data are Fixed Effects (FE) or Random Effects (RE) models (Snijders 2011). While we have identified RE as a theoretically suitable linear panel model approach given our research question, a statistical test is useful to identify any violations of RE model assumptions in our data.

We needed a test for the appropriateness of FE versus RE in the presence of heteroskedasticity. A test of overidentifying restrictions is robust to heteroskedasticity and cluster-dependence, unlike the Hausman test (Arellano 1993).

A standard assumption of panel data models is that error terms are independent across panel entities, e.g., team. Yet there are many practical and theoretical reasons to believe that independence would not hold, particularly amidst the 'unobserved heterogeneity' inherent in social systems (Hoechle 2007). We did a test for cross-sectional dependence in unbalanced panel data (Pesaran 2004). Finally, we tested for the appropriateness of the linear model (Ramsey 1969) while incorporating remedies for AR(1) and/or heteroskedastic error and/or cross-sectional dependence if appropriate based on results from the relevant diagnostic tests described above.

4.6 Hypothesis Testing

4.6.1 Estimation Procedures for Hypothesis Testing

The previous section described our data discovery processes: various tests and procedures to describe our panel data set and to inform model selection. The chapter concludes with a high-level summary of procedures for testing our hypotheses and model evaluation.

In investigating each hypothesis, we created and evaluated graphical displays of the hypothesized relationships. Our first modeling task was estimation of baseline models for both response variables using Ordinary Least Squares (OLS) regression. We regressed both Performance and Innovation on time, innovation process phase, and on a set of background variables. Our background variable choices originated from theoretical insights from previous research and contextual knowledge about teams in this study. From a list of candidate background variables described in section 4.9.4, we selected several predictors to be used with each response variable in testing models that included our substantive network-based predictor variables. We used stepwise procedures (Draper and Smith 2014) and other iterative modeling to assess the extent to which background variables explained variation in our response variables.

We also fit some baseline linear panel models with team-level structure. Panel data (repeated observations of the same entities, e.g. teams) contain two primary sources of variation: (1) systematic differences *between* teams and (2) differences *within* teams that unfold over time. For both performance and innovation, we fit an unconditional means model with no predictors and only team-level random intercepts (Singer and Willett 2003) to assess the extent to which systematic variation in each outcome merits investigation. Using results from these baseline means models, we calculated the interclass correlation coefficient (ICC) to characterize variation in performance and innovation ratings as partitioned *between* teams (regardless of time) or *within* teams over time (Rabe-Hesketh and Skrondal 2008).

Because of the temporal nature of innovation team collaboration and the longitudinal slant of this research, we investigated each of our hypotheses with models that included time as either a predictor or random effect. We also tested each hypothesized relationship without including a time effect and as moderated by innovation process phase. Our candidate linear panel models included Fixed Effects (FE), Random Effects (RE), panel-corrected standard errors (PCSE), and in some cases a linear mixed model combining FE and RE. Specifications for models used to test our hypotheses will be outlined in the next Results chapter.

4.6.2 Model Evaluation

After fitting each model that would contribute to testing of our hypotheses, we conducted a series of post-estimation and testing procedures as appropriate. After each OLS model we examined residual plots, Normal quantile plots, and checked variance inflation factors for sign of multicollinearity (Mansfield and Helms 1982). OLS models were tested with respect to linearity

(Ramsey 1969), homoskedasticity (White 1980), independence (Cochrane and Orcutt 1949), and normality (Shapiro and Wilk 1965), noting any significant departures from model assumptions. OLS model fit was assessed using R^2, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Information Criterion measures are useful for comparison of similar models but not as absolute measures of model fit (Gelman and Hill 2007).

Post-estimation for our PCSE models entailed estimating the correlation matrix of coefficients as well as the $\hat{\Sigma}$ matrix and vector of autocorrelation parameter estimates (Beck and Katz 1995). The PCSE model output contains a Chi-square test that the coefficients are jointly equal to zero, but does not allow calculation of information criterion measures. We use root mean square error (RMSE) as a measure of fit for comparison across each of our candidate model types (Clark and Linzer 2015). RMSE is expressed in response variable units, convenient for interpretation. After fitting mixed models, we reviewed the Chi-square test for model fit, the Likelihood Ratio test for comparison with a basic pooled model, AIC, BIC, and the team-level random effects correlation matrix if appropriate.

4.7 Research Methods Summary

This chapter has described our research context, data sources, and methodological design choices. We tested our hypotheses by analyzing variation in the email communication networks of eleven virtual innovation teams collaborating under the auspices of a large-scale health care system design project. Data were collected primarily from digital archives of email correspondence and from ratings of team performance outcomes from senior leadership. Our data cleaning and analysis occurred in a sequence of stages. We used Condor to analyze raw email data and generate numerical summaries of team networks and communication patterns. We cleaned and organized output from Condor in Excel, then used these quantitative observations as inputs for statistical analysis in STATA. We conducted extensive testing to gain understanding of our panel data and identify optimal modeling choices to handle model error as clustered across teams and time.

The following chapter will summarize our variables as observed in this study, specify models selected to test our hypotheses based on results from diagnostic testing, and present results from estimation models for six hypotheses.

CHAPTER 5: RESULTS

5.1 Descriptive Statistics

This chapter will describe: our panel data structure, preliminary analyses to inform model selection, model specifications used to test hypotheses, and results from testing hypotheses. Variable summaries and descriptive statistics for Response Variables are displayed in Figure 14 and Table 7, respectively.

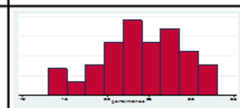
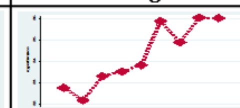
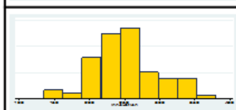
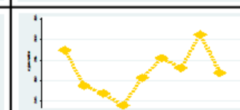
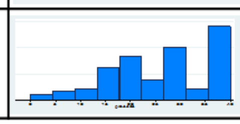
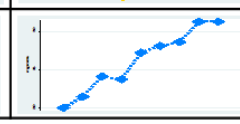
Variable	Operationalization	Reference	Informant	Periodicity	Histogram	Time series all-team average
Work Group Performance	5-point scale rating on 7 dimensions	Cummings & Cross 2003	Project senior leaders	Bi-monthly & quarterly		
Radical Innovation	Point assignment scale (%) with 4 categories	Miron-Spektor, Erez, & Naveh, 2011				
Innovation process scale	40-point checklist with 4 phases	Moen 2002	Team leaders	Monthly		

Figure 14: Summary of Response Variables

Variable	Mean	Median	Standard deviation	IQR	Mini-mum	Maxi-mum	Skew-ness	Kurtosis	Intra-class corre-lation
Work Group Performance	24.2	24	4.9	7.3	13	33	-0.26	2.38	0.52
Radical Innovation	251.8	250	46.8	55.0	135	380	0.23	3.07	0.73
Innovation process scale	25.9	27	10.5	19.0	0	40	-0.17	2.20	0.70

Table 7: Descriptive statistics for Response Variables

Variable summaries and descriptive statistics for Predictor Variables are displayed in Figure 15 and Table 8, respectively.

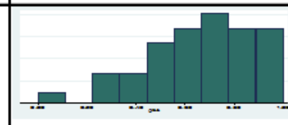
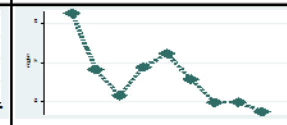
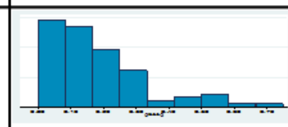
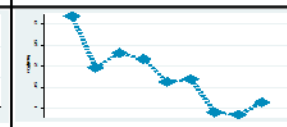
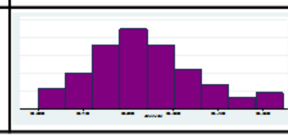
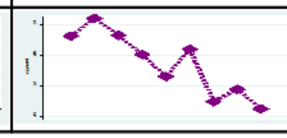
Construct	Variable	Operationalization	Histogram	Time series all-team average
Team Centrality	Group Betweenness Centrality	$\frac{\sum_{i=0}^{g}[C_B'(n^*) - C_B'(n_i)]}{[(g-1)^2(g-2)]/2}$		
Structural Dynamics	Average of the squared weekly changes in GBC	$\frac{\sum_{i=1}^{W}(GBC_w - GBC_{w-1})^2}{Weeks}$		
Participation Equality	Average Weighted Variance in Contribution Index	$\frac{\sum_{i=1}^{T} m_i \cdot var(c_i^{ws})}{\sum_{i=1}^{T} m_i}$		

Figure 15: Summary of Predictor Variables

Construct	Mean	Median	Standard deviation	IQR	Minimum	Maximum	Skewness	Kurtosis	Intra-class corre-lation
Team Centrality	0.67	0.68	0.23	0.30	0.00	1.00	-0.58	3.17	0.169
Structural Dynamics	0.18	0.15	0.15	0.17	0.00	0.75	1.38	4.88	0.162
Participation Equality	0.24	0.24	0.12	0.15	0.00	0.54	0.45	3.06	0.301

Table 8: Descriptive statistics for Predictor Variables

Variable summaries and descriptive statistics for Background Variables are displayed in Figure 14 and Table 7, respectively. Pairwise correlations (and associated p-values) for study variables used to test our hypotheses are displayed in Table 10.

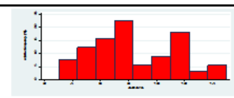
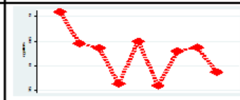
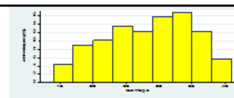
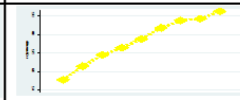
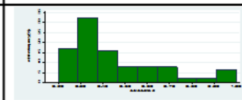
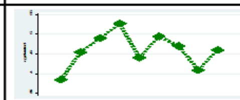
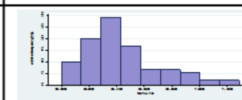
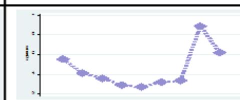
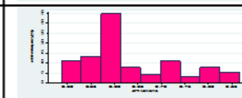
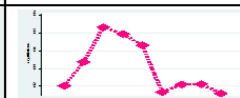
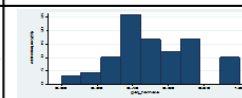
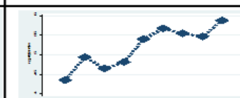
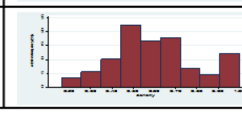
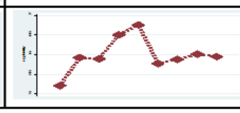
Variable	Operationalization	Histogram	Time series average across teams
Network actors	Count of team members appearing in email network during time period		
Network density	$\frac{\textit{network connections}}{\textit{total potential network connections}}$		
Project duration	Number months since project team inception		
Locations	$\frac{\textit{team member locations}}{\textit{team members}}$		
Team member tenure diversity	$\frac{\sigma_{\textit{team member tenure in months}}}{\mu_{\textit{tenure}}}$		
Status equality	$\frac{\sigma_{\textit{professional status(Low,Medium,High)}}}{\mu\ \textit{status}}$		
Gender distribution	$\frac{\textit{female team members}}{\textit{all team members}}$		

Figure 16: Summary of Background Variables

Variable	Mean	Median	Standard deviation	IQR	Minimum	Maximum	Skewness	Kurtosis
Network actors	8.25	8.00	3.05	5.00	3.00	15.00	0.38	2.13
Network density	0.60	0.57	0.21	0.25	0.16	1.00	0.33	2.51
Project duration	27.9	29.0	6.73	10.0	14.0	41.0	-0.22	2.06
Locations	0.45	0.38	0.22	0.27	0.23	1.00	1.35	3.70
Team member tenure diversity	0.43	0.37	0.29	0.29	0.00	1.29	0.86	3.65
Status equality	0.47	0.47	0.09	0.13	0.31	0.71	0.54	3.01
Gender distribution	0.52	0.50	0.23	0.29	0.00	1.00	0.42	3.10

Table 9: Descriptive statistics for Background Variables

Table 10. Correlation Matrix			1	2	3	4	5	6	7	8	9	10	11	12	13
Response Variables	1	Team Performance	1												
	2	Team Innovation	0.1699	1											
			0.111												
Phase Variable	3	Innovation Process Scale	0.5477*	-0.1121	1										
			<0.001	0.296											
Predictor Variables	4	Team Centrality	0.0643	0.1353	-0.1902	1									
			0.550	0.206	0.074										
	5	Structural Dynamics	-0.0926	0.0156	-0.2294*	0.2494*	1								
			0.388	0.885	0.031	0.018									
	6	Participation Equality	-0.1685	-0.0918	-0.2533*	-0.0591	0.4967*	1							
			0.114	0.392	0.017	0.583	<0.001								
Background Variables	7	Network Actors	0.4182*	0.0735	0.1752	-0.0894	-0.0896	-0.0341	1						
			<0.001	0.493	0.101	0.405	0.404	0.751							
	8	Project Duration	0.1163	-0.0076	0.1527	-0.2648*	-0.3381*	-0.1373	0.0637	1					
			0.278	0.944	0.153	0.012	0.001	0.200	0.553						
	9	Locations	-0.2690*	-0.0063	-0.4666*	0.104	0.4252*	0.4504*	-0.2656*	0.4066*	1				
			0.011	0.953	<0.001	0.332	<0.001	<0.001	0.012	<0.001					
	10	Tenure Diversity	0.1152	0.1900	0.2093*	-0.1205	-0.1367	-0.0352	0.2541*	-0.0465	0.009	1			
			0.282	0.075	0.049	0.261	0.202	0.743	0.016	0.666	0.933				
	11	Status Equality	-0.3114*	0.021	-0.2233*	-0.0489	0.1174	0.1871	-0.3942*	-0.0142	-0.006	0.4570*	1		
			0.003	0.845	0.035	0.649	0.273	0.079	<0.001	0.895	0.956	<0.001			
	12	Gender Distribution	0.2841*	-0.2197*	0.3878*	0.1197	-0.1952	-0.2926*	0.3960*	-0.0755	-0.1889	-0.2888*	-0.5337*	1	
			0.007	0.039	0.000	0.264	0.067	0.005	<0.001	0.482	0.076	0.006	<0.001		
	13	Network Density	-0.062	-0.2064	0.1164	0.0146	-0.1413	-0.3220*	0.2575*	0.1417	-0.0614	0.1961	-0.1307	0.3668*	1
			0.564	0.052	0.277	0.892	0.187	0.002	0.015	0.185	0.568	0.066	0.222	<0.001	

Table 10: Correlation matrix

5.2 Panel Data Structure

Our dataset has an inherent team-level structure, so we used linear panel models to characterize clustering of model errors at different levels of the study design. Our analysis of panel data in STATA began with specification of a cross-panel identifier variable (i.e., team number) for panel entities and a time variable (nine bi-monthly or quarterly time periods from September 2012 until July 2014). Our unit of analysis was the 'team-time' ($n = 89$). We had an unbalanced panel because all of the eleven teams were not represented in each time period (Baltagi and Chang 1994). Initially, we had recorded observations for eight teams in each of the nine time periods, observations for two teams in seven time periods (time 1 – time 7), and observations for one team in six time periods (time 1 – time 6). After exploratory analysis we decided to drop observations of team-time periods in which fewer than 20 email messages were exchanged (as such a sparse network may not be valid for comparison with other network models based on more communication flows). Thus we dropped three observations with fewer than twenty connections from two teams.

We used multiple imputation (Little and Rubin 2014) to generate observations for missing performance and innovation ratings for one team during the first two time periods. Because of an administrative oversight this particular team was not amongst the list of teams provided to senior project leaders for assessment during the first two sets of ratings. The team was active throughout those time periods and there are no special causes that we can find for variation in team outcomes during time 1 and time 2 relative to other times in the observation period. So we can operate as though the data are missing at random (Rubin 1996). Multiple imputation was implemented in

STATA 14 (StataCorp 2015). We simulated plausible values multiple times for missing rating variables, completing twenty copies of the synthetic data set. Each copy was analyzed and estimation results pooled (Royston 2005).

Our final panel consisted of eight teams observed in all nine time periods, one team observed during the first seven time periods, one team observed from the second to seventh time periods, and one team observed during the first four time periods (Figure 17).

```
. xtset team time
       panel variable:  team (unbalanced)
        time variable:  time, 1 to 9
                delta:  1 unit

. xtdescribe

    team:  1, 2, ..., 11                                   n =         11
    time:  1, 2, ..., 9                                    T =          9
           Delta(time) = 1 unit
           Span(time)  = 9 periods
           (team*time uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         4       4       7         9         9       9       9

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+-----------
        8     72.73   72.73 |  111111111
        1      9.09   81.82 |  .111111..
        1      9.09   90.91 |  1111.....
        1      9.09  100.00 |  1111111..
 ---------------------------+-----------
       11    100.00         |  XXXXXXXXX
```

Figure 17: Panel dataset description from STATA

5.2.1 Results from Preliminary and Diagnostic Analysis

As described in the previous Methods chapter, we began exploring our panel dataset with graphical analysis of network models and study measures. Then we conducted a series of evaluative procedures and statistical tests (Table 6) to gain understanding of the error structures in our panel data and thus inform model selection. Results of these tests and procedures are summarized below along with implications for our modeling choices.

Panel data model errors may be clustered over time. First order autocorrelation (AR(1)) indicates correlation between time-adjacent observations (Baltagi and Wu 1999). In other words, AR(1) means that errors in our model today are related to those errors from the previous day, a violation of the independence assumption. We tested for the independence of model error terms using the panel data autocorrelation Durbin-Watson Test (Shehata and Mickaiel 2015a). We found evidence of AR(1) structure for each model tested based on the autocorrelation parameter (rho) computed and the Durbin-Watson test statistic.

We weighed the benefits of a multilevel modeling structure in the presence of background variables, phase indicators, and a time effect with the Breusch and Pagan Lagrangian multiplier test (Breusch and Pagan 1980). The null hypothesis states that the team-level variance components are collectively equal to zero. Rejection of the null hypothesis suggests that the team-level structure is significant. A team-level structure out performed a pooled Ordinary Least Squares (OLS) in each of the models that we tested.

Data with multilevel structure may have model errors with inconsistent levels of variance across entities, violating the OLS assumption of homoskedasticity. We tested for error structure across teams using the residuals of a FE regression model to compute a modified Wald statistic for groupwise heteroscedasticity (Baum 2001). For each model we rejected the null hypothesis of homoscedasticity and concluded that our models needed to accommodate heteroscedasticity-robust standard errors.

If a multilevel modeling structure is appropriate, primary options for panel data are Fixed Effects (FE) and Random Effects (RE) models (Bartels 2008). A FE model examines the extent to which group intercepts differ, assuming constant slopes and variation across groups. A RE model for panel data assumes that unobserved heterogeneity across groups is not correlated with model predictors; the effects themselves are group-specific variance components (Park 2011).

In the Methods chapter we identified RE as a theoretically suitable linear panel approach given our understanding of unobserved variation across teams in the study context and the dual longitudinal and cross-sectional elements of our research question. But a formal statistical test is useful to identify any violations of RE model assumptions in our data. "The crucial distinction between fixed and random effects is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not" (Greene 2003: 347).

Indeed, testing for the appropriateness of FE versus RE is to assess the extent to which model errors are correlated with predictor variables in the model that generated the errors. The Hausman test compares a RE model with a FE model using the same set of predictors with the null hypothesis that group-level variance components are not correlated with the model predictors (Hausman 1978). The Hausman test is popular but not consistent in the presence of heteroskedasticity (Arellano 1993). Instead we used a test of over-identifying restrictions (Schaffer and Stillman 2015), asymptotically equivalent to the Hausman test under conditional homoskedasticity but also extendable to accommodate heteroskedatic and clustered error across panel members (Baum et al. 2007).

Results of the test of over-identifying restrictions supported RE for nine of the twelve structural and temporal models tested. Each of the six models (hypotheses ‘b’) with moderating effects of innovation process phase indicated that FE was appropriate. Given the solid support of RE by the other models tested and our theoretical rationale for using RE, we feel confident in applying random intercepts in models used to test the moderating effects of innovation process phases (hypotheses ‘b’).

A standard assumption of panel data models is that error terms are independent across panel members, i.e. teams in this study. Yet there are many practical and theoretical reasons to believe that independence would not hold, particularly amidst the ‘unobserved heterogeneity’ inherent in social systems (Hoechle 2007). Cross-sectional dependence in panel data may emerge in spatial diffusion patterns, via unobserved common influences, or as non-stationarity (Chudik et al. 2011; Holly et al. 2011; Pesaran et al. 2013). It seems likely that unobserved common influences could influence C3N Project teams. Potential sources of cross-sectional dependence in our panel data include overlapping team membership. Also, teams operated as separate units but under the auspices of a large grant project. The eleven teams shared senior project leaders, interacted on all-team online meetings and periodic face-to-face meetings, and used similar frameworks such as the innovation process phase checklist. We assessed the extent of cross-sectional dependence using a test that accommodates unbalanced panel data (Pesaran 2004). The null hypothesis of no cross-sectional dependence was supported at the $\alpha < 0.05$ significance level for all but one of our models. However, fourteen of the eighteen models tested produced marginally significant p-values ranging from 0.05 – 0.16. Such results could be interpreted as inconclusive given our theoretical reasons to expect dependence across teams. Thus we should consider a model that can accommodate cross-team clustering of errors.

On the other hand, any cross-sectional dependence that is present seems relatively innocuous. Along with the Pesaran test, we calculated the average absolute value of off-diagonal elements in the correlation matrix of residuals (De Hoyos and Sarafidis 2006) and observed low correlations ranging from 0.33 – 0.44 ($\bar{\rho} = 0.38$). Hence models that do not explicitly treat cross-sectional dependence still merit consideration in this study.

Finally, we tested the linearity regression assumption with Ramsey's Regression Equation Specification Error Test (RESET) for panel data (Ramsey 1969; Shehata and Mickaiel 2015b). For each hypothesis we fit response variables, predictor variables, and primary background variables to four models to be tested with RESET: (i) FE, (ii) RE, (iii) AR(1), and (iv) panel-corrected standard errors (PCSE), which incorporates AR(1), heteroscedasticity, and cross-sectional dependence. Then Ramsey's procedure tests whether non-linear combinations of fitted model values have explanatory power for the response variables, in which case a violation of the linearity specification is likely. Results from our RESET testing favor the fourth model, PCSE; it passed across the board for each of our models tested. This result is consistent with results from our other tests which indicated the presence of AR(1), heteroscedasticity, and some level of cross-sectional dependence.

So far, this chapter has summarized the preliminary tests and analyses described in the previous Methods chapter as they apply to our observed data. Panel data tests suggest that our model error structures are overwhelmingly AR(1), heteroskedastic, and potentially correlated across teams. This information is helpful as we specify estimation procedures for testing of study hypotheses. Statistical tests also point to the appropriateness of modeling random effects (RE), concurring with our theoretical reasoning for this modeling approach. RE models are suitable for analysis when a research question has dual cross-sectional and temporal elements.

Informed by theory and our diagnostics, we tested our hypotheses using two primary modeling approaches: linear regression with panel-corrected standard errors (PCSE) and Maximum Likelihood mixed models with random team variance components (RE). Both models accommodate AR(1) and heteroscedasticity; the PCSE model also incorporates cross-sectional dependence.

The next section will outline our baseline modeling approach, followed by specification of the two primary models used for estimation. The chapter concludes with summary of our results from testing six hypotheses.

5.2.2 Baseline Modeling

Baseline models for response variables are useful for comparison with subsequent models containing predictor variables of interest to the research team. Tables 11 and 12 display baseline models for Performance and Innovation, respectively.

PERFORMANCE	1. OLS and time		2. OLS and phases		3. OLS and controls		4. PCSE with time		5. PCSE with phase		6. PCSE with controls		7. Mixed "means" model		8. Mixed "growth" model	
Time	**0.261**	*0.013*					**0.283**	*< 0.001*							**0.215**	*0.005*
Design			**-0.512**	*< 0.001*					**-0.494**	*< 0.001*						
Prototype			**-0.439**	*< 0.001*					**-0.308**	*0.007*						
Pilot			**-0.196**	*0.061*					-0.159	*0.290*						
Implement																
Actors					**0.419**	*< 0.001*					**0.322**	*0.011*				
Duration					**0.255**	*0.009*					**0.423**	*< 0.001*				
Status					**-0.222**	*0.024*					**-0.238**	*0.014*				
Constant	4.428	*< 0.001*	3.267	*< 0.001*	3.891	*< 0.001*	4.309	*< 0.001*	5.271	*< 0.001*	3.534	*< 0.001*	4.843	*< 0.001*	4.443	*< 0.001*
Model F test	6.371	0.013	12.76	*< 0.001*	10.71	*< 0.001*										
r2	0.068		0.311		0.274											
Root Mean Square Error	4.76		4.15		4.25		3.37		3.25		3.39		3.450		3.24	
chi2							20.12	*< 0.001*	48.20	*< 0.001*	37.36	*< 0.001*	.		7.72	*0.005*
log likelihood	-264.2		-250.8		-253.1								-249.0		-244.6	
AIC	532.4		509.6		514.2								504.0		499.2	
BIC	537.4		519.6		524.1								511.5		511.6	
rho							0.500**		0.491**		0.463**		0.522		0.536	
sd_Ui													3.610		3.485	
SE(sd_Ui)													0.873		0.870	
sd_Time															0.167	
SE(sd_Time)															0.261	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 11: Baseline modeling for Performance Variable

INNOVATION	1. OLS and time		2. OLS and phases		3. OLS and controls		4. PCSE with time		5. PCSE with phase		6. PCSE with controls		7. Mixed "means" model		8. Mixed "growth" model	
Time	0.035	*0.746*					0.017	*0.813*							0.025	*0.751*
Design			-0.123	*0.254*					**-0.164**	*< 0.001*						
Prototype			**0.294**	*0.014*					0.088	*0.260*						
Pilot			0.219	*0.065*					0.041	*0.724*						
Implement																
Status					0.051	*0.648*					0.093	*0.181*				
Tenure					0.171	*0.137*					0.090	*0.183*				
Density					-0.164	*0.139*					-0.127	*0.052*				
Constant	5.311	*< 0.001*	4.535	*< 0.001*	5.327	*< 0.001*	*5.189*	*0.000*	*5.231*	*0.000*	*5.032*	*0.000*	5.369	*< 0.001*	5.319	*< 0.001*
Model F test	0.106	*0.746*	3.659	*0.016*	2.047	*0.113*										
r2	0.001		0.114		0.067											
Root Mean Square Error	47.06		44.83		46.01		25.31		24.52		25.40		23.32		20.55	
chi2							0.056	*0.813*	32.34	*< 0.001*	6.719	*0.081*	.		0.101	*0.751*
log likelihood	-468.1		-462.7		-465.0								-423.7		-421.1	
AIC	940.1		933.4		938.0								853.5		852.1	
BIC	945.1		943.4		948.0								861.0		864.5	
rho							0.619**		0.550**		0.645**		0.734		0.835	
sd_Ui													38.69		46.19	
SE(sd_Ui)													8.593		10.99	
sd_Time															3.751	
SE(sd_Time)															1.414	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 12: Baseline modeling for Innovation Variable

We used OLS and PCSE regression to model response variables performance and innovation (separately) as a function of time and innovation process phase. We also regressed each response variables on a set of background variables (Figure 16 and Table 10). We selected background variables based on theoretical insights from previous research as well as results from stepwise regression (Draper and Smith 2014). Outstanding predictors of Work Group Performance included network actors, project duration, and status equality. The Radical Innovation measure was best explained by variation in individual team member tenure, status equality, and network density.

We also assessed baseline variation in performance and innovation using linear mixed models that included fixed effects as well as random team intercepts. The unconditional growth model (Singer and Willett 2003) is a baseline RE model for change in which time is the only predictor and the constant represents the mean value of the response variables at the 'beginning of time'. The unconditional means model fits random team intercepts but no other predictors, holding slope constant at zero (Singer and Willett 2003).

5.2.3 Within- and Between-Team Variation

Our baseline modeling was focused on understanding how our response variables vary across teams and over time, before incorporating our network-based predictors. But we also fit the unconditional means model to each of our three predictor variables and the innovation process variable to gain understanding of variance in each. Our panel data have two sources of variation: (1) teams are systematically different from each other (*between*-team variation) and (2) team activities and attributes may vary over time (*within*-team variation) (Hsiao 2014). From the means model we estimated the intraclass correlation coefficient, the proportion of total variance in the response variables that occurs *between* teams (Cameron and Trivedi 2005). Assessment of within- and between-team variation was insightful with respect to our model choices and offers further support of our inclination towards RE.

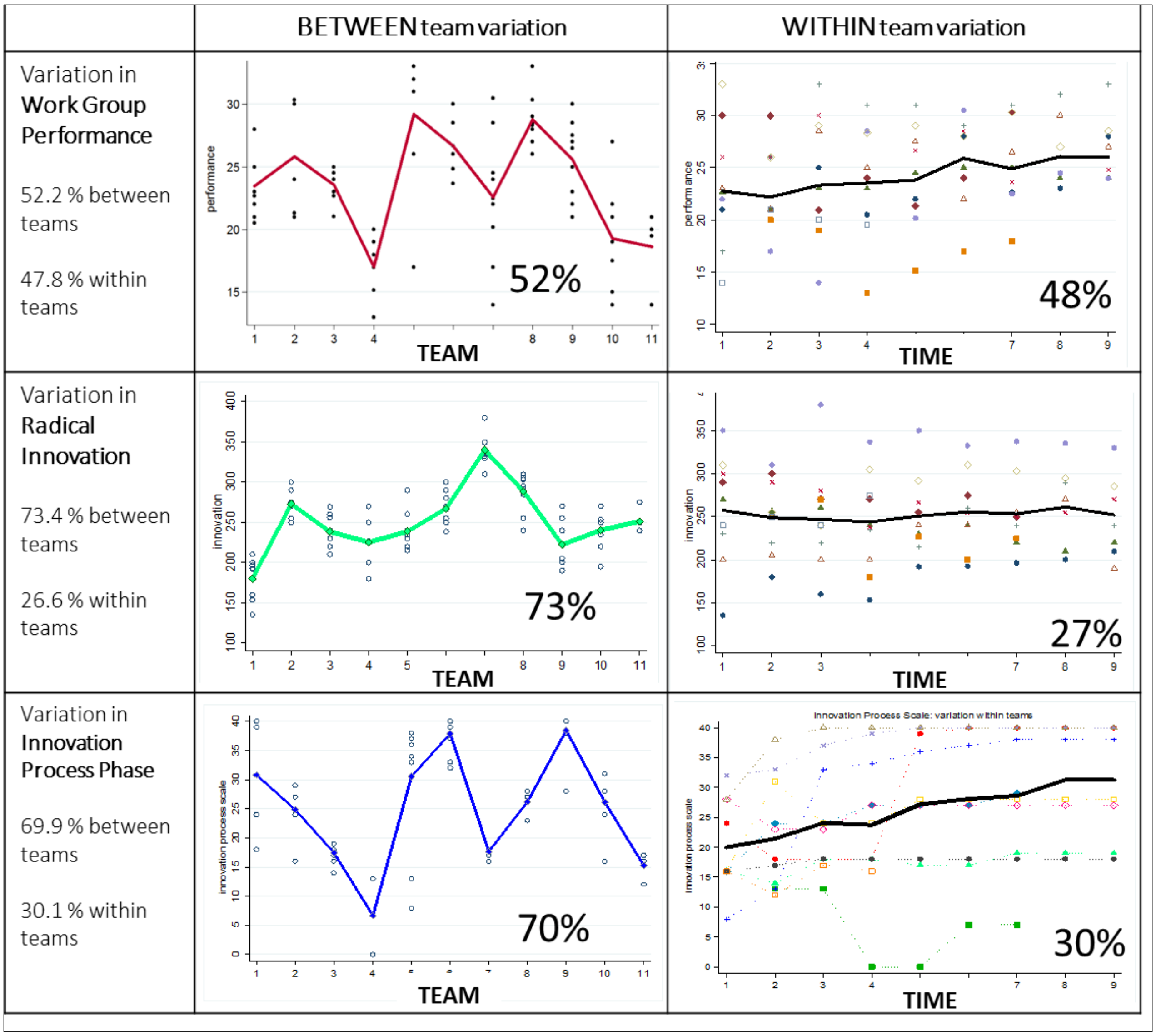


Figure 18: Between- and within-team variation for response variables and process variable

The bulk of the variance in our response variables and in the innovation process phase variable lies *between* teams (Figure 18). There are time-invariant characteristics that place teams at different levels. It is interesting to note that our most of the variance in our network-based predictor variables (Figure 19) emerges *within* teams over time.

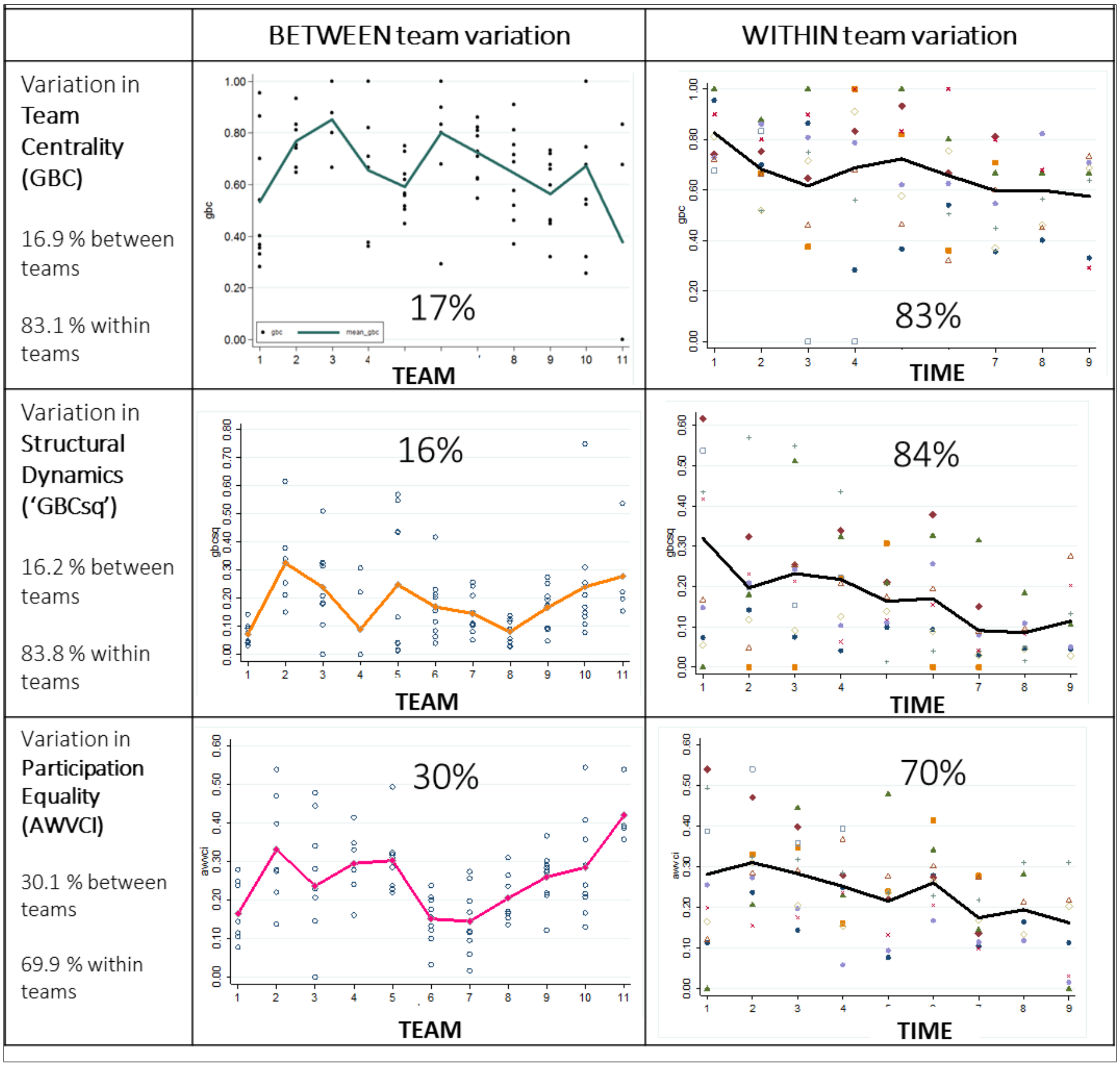


Figure 19: Between- and within-team variation for predictor variables

But the dominance of between-team variation in our response variables and process variable offers evidence of superiority of the RE model. The FE model uses only within variance for estimation and disregards between variance (Wooldridge 2010) and is thus an inefficient approach (Plümper and Troeger 2007).

5.3 Model Specification for Hypothesis Testing

This chapter has described our panel data set and variables as observed. Results from preliminary analyses were presented along with implications for our modeling choices. This section will outline the two models used to formally test hypotheses in this study: (1) linear regression with panel-corrected standard errors (PCSE) and (2) the linear mixed model with random intercepts.

5.3.1 Prais-Winsten Regression with Panel-Corrected Standard Errors

Diagnostic tests suggested that our data exhibited non-constant error variance with a certain extent of cross-sectional dependence. Heteroskedasticity can be managed with robust standard errors (Long and Ervin 2000). Contemporaneous correlation of errors across teams (i.e., cross-sectional dependence) in our dataset can be accounted for with robust PCSE averaging within-team errors over time (Beck and Katz 1995). We also observed that our data were dependent over time, AR(1). Thus we used STATA's *xtpcse* routine to calculate PCSE estimates for parameters generated by Prais-Winsten regression, which uses generalized least-squares to estimate the parameters in linear regression models in which errors are AR(1). We invoked the option to model panel-specific AR(1), modeling distinctions in error structure across teams after observing variation across teams with respect to the autocorrelation coefficient.

We applied this PCSE Prais-Winsten model to test our "a" hypotheses about the effect of predictor variables on response variables. Recall that most of these hypotheses tested as RE-appropriate. The PCSE model is based on a pooled regression estimator which is inconsistent with a FE structure but appropriate with RE as long as PCSE are used for inference (Cameron and Trivedi 2005). We fit PCSE models both with and without a time effect to gain understanding of how the impact of our network-based variables might change when time is modeled explicitly. The PCSE model specification is:

$$Y_{it} = \beta_0 + \beta_1 x1_{it} + \beta_2\, x2_{it} + \beta_3\, x3_{it} + \epsilon_{it}$$

where ϵ_{it} is an error term that may be autocorrelated along *t* time periods or contemporaneously correlated across *i* teams.

5.3.2 Linear Mixed Model

The second ('b') portion of each of our six hypotheses also considered the innovation process phase (as described in the previous Methods chapter) in which each team was situated. These models tested the contingency effects of the various stages in an innovation team's lifespan and how different stages might affect how team centrality, structural dynamics, and participation equality influence team outcomes.

Recall that during our exploratory analyses we observed that models for our "b" hypotheses about the moderating effects of innovation process phase indicated that the FE model was appropriate. We used linear mixed models with maximum likelihood estimation to test our hypotheses addressing phase effects. The STATA *mixed* routine implements linear models with both fixed and random effects and can accommodate AR(1) as well as heteroscedasticity (Gutierrez and StataCorp 2006). The FE are estimated directly and interpreted as analogous to basic regression coefficients. RE are summarized as variance components and may be either random intercepts or random coefficients; these are intercepts and slopes that can vary across teams in our sample. The mixed model is specified as:

$$Y_{ij} = \beta_0 + \beta_1 x1_{ij} + \beta_2\, x2_{ij} + \beta_3\, x3_{ij} + \upsilon_{0j} + \epsilon_{ij}$$

where $\epsilon_{ij} = \phi_1 \epsilon_{i-1,j} + u_{ij}$ and u_{ij} are independent and identically distribution Gaussian with mean zero and variance σ_u^2 and ϕ_1 is the correlation between successive error terms. Constant β_0 is mean of team-level random intercepts. Each of *j* teams also has their own intercept random intercept υ_{0j}.

Testing Hypothesis 4, we fit a mixed model with random team intercepts as above with a fixed effect for the interaction between our 'GBCsq' measure with time and also a random effect that allows the slope of time to vary across teams. That model is specified as:

$$Innovation_{ij} = \beta_0 + \beta_1 GBCSQ_{ij} + \beta_2\, Status_{ij} + \beta_3\, Actors_{ij} +$$

$$\beta_4\, Duration_{ij} + \beta_5\, GBCSQ * TIME_{ij} + \upsilon_{0j} + \upsilon_{1j} TIME_{ij} + \epsilon_{ij}$$

with the same specification as above for stochastic component of the within-team model (i.e., ϵ_{ij}).

5.3.3 Hypothesis Testing with Innovation Process Phases

Our observations are well-distributed across all innovation process phases except for disproportionately few in the initial design phase (Table 13). This makes sense given that our observation period overlapped with the final two years of a five-year grant period, although it is unfortunate that we have limited insight into the earliest stage based on results from this study.

We chose the fourth phase, Implement, as the base level in our models testing for the contingency effects of innovation process phases. Implementation makes a good base level as the final phase, and also because it is reasonable to assume that this phase most closely resembles most virtual team work outside of the innovation context.

Phase	Frequency	Percent
(1) Design	5	5.62
(2) Prototype	30	33.71
(3) Pilot	24	26.96
(4) Implement	30	33.71
Total	89	100

Table 13: Innovation Process Phase variable as distributed in our sample

5.4 Results from Hypothesis Testing

In the following section, model tables reporting results for each hypothesis display standardized beta coefficients and one-tailed p-values as appropriate for our directional hypotheses. Coefficients referenced in the text are also standardized, representing the change in standard deviation (SD) of the response variables for a one-SD increase in the predictor variables.

5.4.1 Team Centrality and Work Group Performance

Hypothesis 1a predicted a negative relationship between team centrality and performance and was not supported. Contrary to expectations, we observed a positive and significant association with and without a time effect. Model 5 results (Table 14) indicate that GBC is positively related to team performance ($\beta = 0.296, p = 0.04$) while controlling for network actors, project duration, status equality, and time. For a one-SD increase in GBC, we expect about a 3/10$^{\text{ths}}$-SD increase in performance (1.45 points on a 28-point scale and 7.3% of the observed range of the performance rating variable). The interaction between GBC and time was negative and not significant ($\beta = -0.219, p = 0.42$).

Hypothesis 1b, for which we observed limited partial support in design phase, predicted that innovation process phase would moderate the negative relationship between team centrality and work group performance. As depicted with phase-specific and pooled OLS regressions in Figure 20, the association between GBC and performance does change as a function of innovation process phase, just not in the direction we anticipated. In Model 6 (Table 14), controlling for network actors, project duration, and status equality, we observed a positive and significant relationship ($\beta = 0.374, p < 0.01$) during pilot and implementation phase.

Dependent Variable	PERFORMANCE	4. Panel-corrected standard errors		5. PCSE with time		6. Mixed effects with phases	
Independent Variables	GBC	**0.156**	*0.066*	**0.296**	*0.035*	**0.374**	*0.001*
	Actors	**0.316**	*0.011*	**0.300**	*< 0.001*	**0.351**	*0.012*
	Duration	**0.462**	*< 0.001*	**0.076**	*0.001*	**0.325**	*0.000*
	Status	**-0.234**	*0.014*	**-0.196**	*0.015*	**-0.194**	*0.015*
Time	Time			0.023	*0.940*		
	GBC # Time			-0.219	*0.424*		
Intercept adjustments by phase	Design					**-0.217**	*0.005*
	Prototype					0.181	*0.170*
	Pilot					-0.323	*0.037*
	Implement					-	-
Slope adjustments by phase	Design # gbc					**-0.442**	*0.000*
	Prototype # gbc					**-0.311**	*0.005*
	Pilot # gbc					-0.011	*0.232*
	Implement # gbc					-	-
	Constant	**2.946**	*< 0.001*	**2.258**	*0.011*	**3.049**	*0.003*
Model fit and summary statistics	Model F test						
	Model chi2 test	19.51	*< 0.001*	26.57	*< 0.001*	1,734,807	*< 0.001*
	Root Mean Square Error	3.747		3.751		2.736	
	rho	0.480**		0.508**		-0.161	
	log likelihood					-223.2	
	aic					466.4	
	bic					491.3	
Random Effects	sigma_Ui					1.588	
	SE(sigma_Ui)					0.400	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

One-tailed p-values are reported.

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 14: Results from testing Hypotheses 1a and 1b

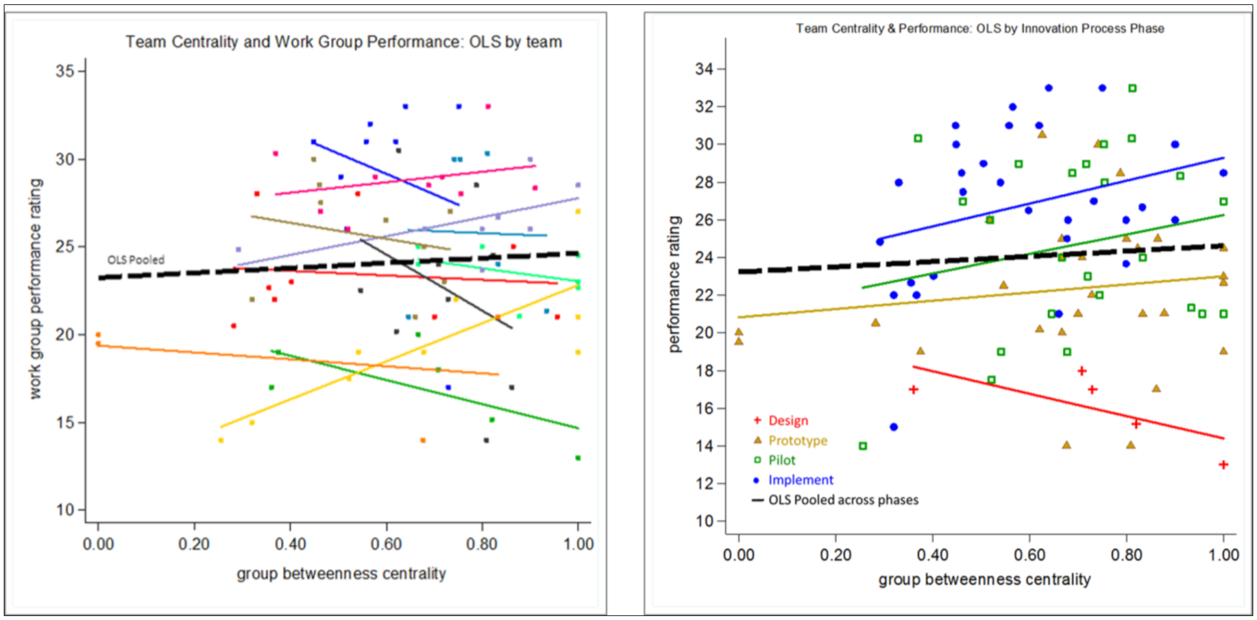


Figure 20: Graphical display of results from testing Hypotheses 1a and 1b

These are phases three and four, in which we expect an almost 1/5th-SD increase in performance (1.84 points on a 28-point rating scale and 9.2% of the observed range of the performance rating variable) for a one-SD increase in GBC. Model 6 shows a negative and significant slope adjustments for the prototype phase ($\beta = -0.311 + 0.374, p < 0.01$), resulting in a weaker positive association. We observed a negative and significant association during the initial design phase ($\beta = -0.442 + 0.374, p < 0.01$). However, our final panel contained merely five 'team*time' observations during design phase (5.62% of our total n = 89). So while it totally makes sense that the impact of team centrality would differ in the early stages of an innovation project, we have limited insight into design phase and should interpret this and any other design phase-specific findings with caution.

5.4.2 Team Centrality and Radical Innovation

Hypothesis 2a predicted a negative relationship between team centrality and innovation and was not supported. We observed an interesting effect between GBC and time as they interact to impact team innovation. Table 15 displays Model 5 results, controlling for diversity in team member tenure, status equality, network density, and time. Figure 21 displays results graphically with linear regression models for each team and each innovation process phase.

Contrary to what we expected, GBC was positively and significantly associated with radical innovation ($\beta = 0.202, p = 0.04$). For every one-SD increase in GBC, we expect just over a 1/5th-SD increase in innovation (almost ten points on a 300-point scale and 3.9% of the observed range of the innovation rating variable). Model 5 also estimates the interaction between GBC and time ($\beta = -0.418, p = 0.03$). For each increase in time, we expect the slope of GBC to decrease by 0.4 (almost 20 points on a 300-point scale and 8% of the observed range of the innovation rating variable). It seems that our hypothesized negative relationship between GBC and innovation may emerge over time.

Hypothesis 2b, partially supported, predicted that innovation process phase would moderate the negative relationship between team centrality and radical innovation. Table 15 and Figure 21 display results for Model 6 (controlling for tenure diversity, status equality, and network density), in which we observed a negative and significant relationship between GBC and innovation at the base level ($\beta = -0.218, p = 0.05$). The prototype phase slope is not distinguishable from that of implementation phase. During prototype and implementation phases, we expect about a 1/5th-SD decrease in innovation for a one-SD increase in GBC. Slope adjustments for design phase

$(\beta = 0.368 - 0.218, p = 0.01)$ and pilot phase $(\beta = 0.293 - 0.218, p = 0.02)$ are significant, adding to the base level slope such that GBC and innovation are positively but weakly associated.

Dependent Variable	INNOVATION	4. Panel-corrected standard errors		5. PCSE with time		6. Mixed effects with phases	
Independent Variables	GBC	-0.024	*0.343*	**0.202**	*0.039*	**-0.218**	*0.045*
	Tenure	0.089	*0.094*	0.067	*0.162*	**0.101**	*0.026*
	Status	0.081	*0.128*	0.054	*0.223*	0.057	*0.198*
	Density	**-0.119**	*0.025*	**-0.125**	*0.020*	**-0.140**	*0.031*
Time	Time			**0.390**	*0.030*		
	GBC # Time			**-0.418**	*0.028*		
Intercept adjustments by phase	Design					**-0.414**	*0.002*
	Prototype					-0.220	*0.173*
	Pilot					**-0.443**	*0.002*
	Implement					-	-
Slope adjustments by phase	Design # gbc					**0.368**	*0.008*
	Prototype # gbc					0.190	*0.118*
	Pilot # gbc					**0.293**	*0.018*
	Implement # gbc					-	-
	Constant	5.184	*< 0.001*	4.693	*< 0.001*	5.987	*< 0.001*
Model fit and summary statistics	Model F test						
	Model chi2 test	6.697	*0.153*	16.46	*0.0115*	945462.4	*< 0.001*
	Root Mean Square Error	25.88		25.72		21.26	
	rho	0.595**		0.597**		0.252	
	log likelihood					-411.8	
	aic					843.5	
	bic					868.4	
Random Effects	sigma_Ui					38.88	
	SE(sigma_Ui)					9.40	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

One-tailed p-values are reported.

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 15: Results from testing Hypotheses 2a and 2b

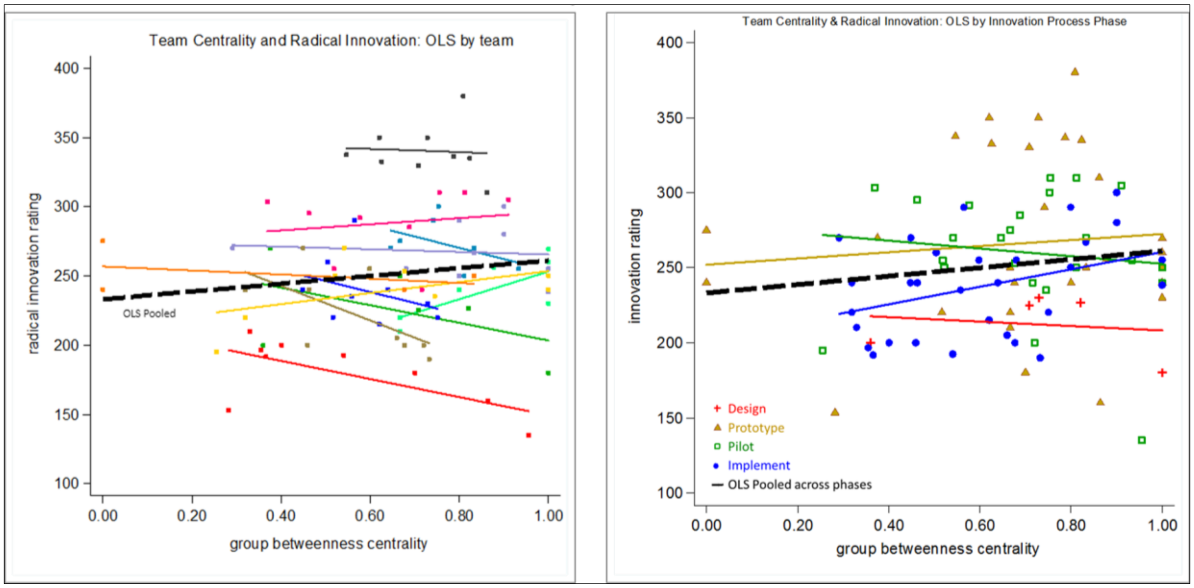


Figure 21: Graphical display of results from testing Hypotheses 2a and 2b

5.4.3 Structural Dynamics and Work Group Performance

Hypothesis 3a predicted a positive relationship between structural dynamics ('GBCsq') and team performance and was not supported. As shown in Table 16, we observed an extremely weak and positive association ($\beta = 0.038, p = 0.33$) in Model 4 without a time effect. Including a time effect produces an extremely weak and negative association ($\beta = -0.081, p = 0.26$) in Model 5. The Model 5 interaction effect for GBCsq and time is positive but not significant ($\beta = 0.140, p = 0.15$). Figure 22 displays results graphically with linear regression models for each team and each innovation process phase.

Hypothesis 3b stated that innovation process phase would moderate the positive relationship between GBCsq and performance. Table 16 displays results indicating partial support of our hypothesis in Models 6 and 7. Model 7 contains random slopes and intercepts for innovation phases and an extended set of background variables.

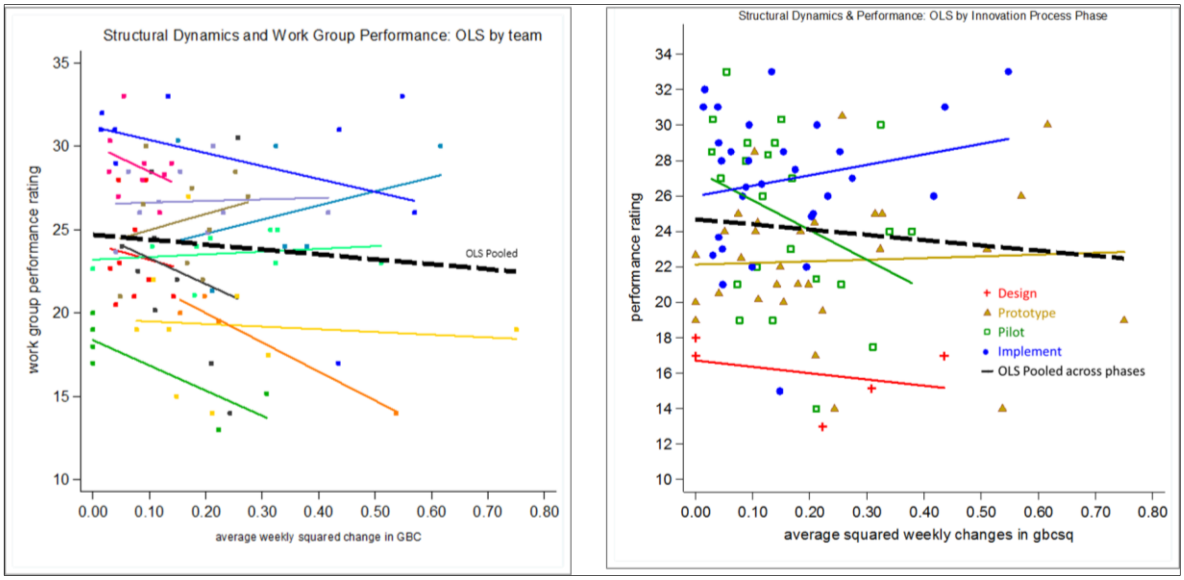


Figure 22: Graphical display of results from testing Hypotheses 3a and 3b

Controlling for actors, project duration, status equality, locations, tenure diversity, and gender distribution, we found support for our hypothesis during the implementation phase base level ($\beta = 0.210,\ p < 0.001$). For every one-SD increase in GBCsq, we expect a 2/10th-SD increase in performance (one point on a 28-point scale and 5.2% of the observed range of the performance rating variable). Slope adjustments for other phases are significant and result in negative slopes (Figure 22), indicating that the positive relationship that we predicted may only hold during implementation phase.

Dependent Variable	PERFORMANCE	4. Panel-corrected standard errors		5. PCSE with time		6. Mixed effects with phases		7. Mixed effects with phases, additional controls	
Independent Variables	Avg Δ gbc^2	0.038	*0.331*	-0.081	*0.258*	**0.211**	*< 0.001*	**0.210**	*< 0.001*
	Actors	**0.329**	*0.010*	**0.342**	*0.005*	**0.254**	*0.044*	**0.347**	*0.019*
	Duration	**0.436**	*< 0.001*	**0.443**	*0.031*	**0.279**	*0.004*	**0.386**	*0.007*
	Status	**-0.235**	*0.008*	**-0.229**	*0.012*	**-0.246**	*0.005*	**-0.205**	*0.023*
	Locations							0.167	*0.137*
	Tenure							-0.063	*0.103*
	Female							0.191	*0.058*
Time	Time			-0.122	*0.291*				
	Δ gbc^2 # time			0.140	*0.150*				
Intercept adjustments by phase	Design					**-0.412**	*< 0.001*	**-0.405**	*< 0.001*
	Prototype					-0.116	*0.150*	-0.118	*0.176*
	Pilot					0.021	*0.416*	0.020	*0.413*
	Implement					-	-	-	-
Slope adjustments by phase	Design # Δ gbc^2					**-0.304**	*< 0.001*	**-0.467**	*0.001*
	Prototype # Δ gbc^2					**-0.166**	*0.029*	**-0.157**	*0.060*
	Pilot # Δ gbc^2					**-0.421**	*0.002*	**-0.350**	*0.006*
	Implement # Δ gbc^2					-	-	-	-
	Constant	3.396	*0.001*	3.530	*0.001*	4.498	*0.000*	3.049	*0.038*
Model fit and summary statistics	Model F test								
	Model chi2 test	38.50	*< 0.001*	46.98	*< 0.001*	238,708	*< 0.001*		
	Root Mean Square Error	3.396		3.465		2.853		2.831	
	rho	0.457**		0.437**		-0.063		-0.063	
	log likelihood					-227.6		-225.8	
	aic					475.3		471.6	
	bic					500.2		496.5	
Random Effects	sigma_Ui					1.777		1.531	
	SE(sigma_Ui)					0.435		0.384	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

One-tailed p-values are reported.

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 16: Results from testing Hypotheses 3a and 3b

5.4.4 Structural Dynamics and Radical Innovation

Hypothesis 4a, predicting a positive relationship between structural dynamics and radical innovation, was supported alongside a time effect. Displayed in Table 17 are results for Model 5 (controlling for status equality, network actors, and project duration), in which we observed a mild but significant positive association ($\beta = 0.123,\ p = 0.03$). Figure 23 displays results graphically with linear regression models for each team and each innovation process phase.

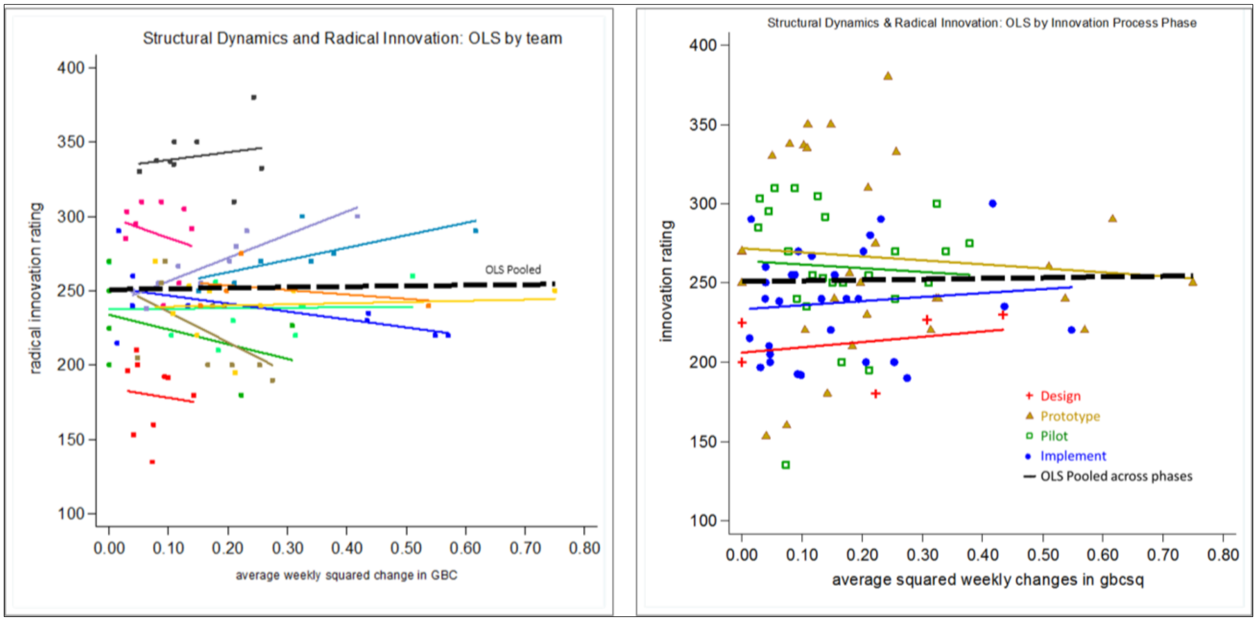


Figure 23: Graphical display of results from testing Hypotheses 4a and 4b

For a one-SD increase in GBCsq, we expect just over a $1/10^{th}$-SD increase in innovation (about 5.8 points on a 300-point scale and 2.4% of the observed range of the innovation rating). Model 5 also has miniscule but significant effects for time ($\beta = 0.015,\ p = 0.05$) and the GBCsq*time interaction ($\beta = 0.031, p = 0.05$).

Model 6 (Table 17) differs from Model 5 in that time is included as a RE: variance components allow the slope of time to vary randomly across teams. Here we see GBCsq positively associated with innovation ($\beta = 0.194,\ p \leq .01$) and a negative interaction between GBCsq and time ($\beta = -0.213,\ p = 0.01$). In Model 6, we expect an almost $1/5^{th}$-SD increase in innovation ratings (just over 9 points on a 300-point scale and 3.7% of the observed range of the innovation rating) for a one-SD increase in GBCsq. Figure 23 displays results graphically with linear regression models for each team and each innovation process phase.

Hypothesis 4b predicted that innovation process phase would moderate the positive relationship between structural dynamics and radical innovation. Model 7 in Table 17 controls for tenure diversity, status equality, and network density as well as random intercept and slope adjustments by phase; here we do not observe a significant association between GBCsq and innovation during prototype (phase 2) or implementation (phase 4). In partial support of our hypothesized relationship, Model 7 estimates a positive slope during the under-represented design phase ($\beta = 0.441 - 0.06,\ p = 0.01$) and during pilot phase ($\beta = 0.340 - 0.06,\ p = 0.04$), where we expect just under a 3/10th-SD increase in innovation (about 13 points on a 300-point rating scale and 5.4% of the observed range for the innovation rating variable) for a one-SD increase in GBCsq.

Testing for Hypothesis 4a revealed an enhanced relationship between structural dynamics and innovation when time was included in the model. So we tried again modeling time as a random effect and its interaction with GBCsq as a fixed effect (alongside slope and intercept adjustments by phase and controlling for project duration).

With Model 8 in Table 17, we again observed the hypothesized relationship to be more pronounced when the GBCsq/time interaction is modeled explicitly and the slope of time is allowed to vary randomly across teams. Model 8 shows a positive and marginally significant association during the implementation phase base level as well as prototype phase ($\beta = 0.290,$ $p = 0.06$). During pilot phase, we expected an increase in innovation ratings of almost 7/10th SDs (almost 32 points on a 300-point scale and 13% of the observed range for the innovation rating variable) for a one-SD increase in GBCsq ($\beta = 0.392 + 0.290,\ p = 0.03$).

Dependent Variable	INNOVATION	5. PCSE with time		6. Mixed model with time RE		7. Mixed model with phases		8. Mixed model with phases and time	
Independent Variables	Avg Δ gbc^2	**0.123**	*0.027*	**0.194**	*0.014*	-0.060	*0.347*	0.290	*0.056*
	Tenure					**0.120**	*0.024*		
	Status	**0.183**	*0.031*	0.083	*0.065*	**0.076**	*0.034*		
	Density					-0.123	*0.054*		
	Actors	0.000	*0.233*	-0.147	*0.090*				
	Duration	-0.004	*0.099*	0.151	*0.166*			0.006	*0.058*
Time	Time	**0.015**	*0.048*						
	Δ gbc^2 # time	-0.031	*0.052*	**-0.213**	*0.013*			**-0.086**	*0.013*
Intercept adjustments by phase	Design					**-0.352**	*< 0.001*	**-0.258**	*< 0.001*
	Prototype					-0.050	*0.349*	-0.017	*0.343*
	Pilot					**-0.301**	*0.022*	**-0.109**	*0.015*
	Implement					-	-	**-**	-
Slope adjustments by phase	Design # Δ gbc^2					**0.441**	*0.005*	**0.404**	*0.016*
	Prototype # Δ gbc^2					0.042	*0.390*	-0.049	*0.355*
	Pilot # Δ gbc^2					**0.340**	*0.037*	**0.392**	*0.032*
	Implement # Δ gbc^2					-	-	-	-
	Constant	5.009	*< 0.001*	4.721	*< 0.001*	5.389	*< 0.001*	4.487	*< 0.001*
Model fit and summary statistics	Model F test								
	Model chi2 test	6.355	*0.385*	18.269	*0.003*	28,556.9	*< 0.001*	83,745.1	*< 0.001*
	Root Mean Square Error	25.72		18.68		21.80		18.96	
	rho	0.654**		-0.125		0.344		0.081	
	log likelihood			-417.6		-411.0		-411.8	
	aic			855.1		842.0		843.6	
	bic			880.0		866.9		868.5	
Random Effects	sd_Ui			50.23		38.763		45.390	
	SE(sd_Ui)			11.47		9.683		18.432	
	sd_Time			4.500				2.843	
	SE(sd_Time)			1.143				3.374	

n = 89
Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).
One-tailed p-values are reported.
** Panel-specific Autocorrelation; average team AR(1) displayed

Table 17: Results from testing Hypotheses 4a and 4b

5.4.5 Participation Equality and Work Group Performance

Hypothesis 5a predicted a positive association between participation equality and performance (represented statistically with a negative association between the AWVCI measure and performance ratings). Our hypothesized relationship was not supported. As displayed in Table 18, we observed an extremely weak negative relationship with Model 4 ($\beta = -0.015, p = 0.40$) and again alongside time in Model 5 ($\beta = -0.083, p = 0.24$). The AWVCI/Time interaction term in Model 5 was weakly positive and not significant ($\beta = 0.060, p = 0.29$).

Dependent Variable	PERFORMANCE	4. Panel-corrected standard errors		5. PCSE with time		6. Mixed effects with phases	
Independent Variables	AWVCI	-0.015	*0.404*	-0.083	*0.239*	**0.444**	*0.001*
	Actors	**0.324**	*0.005*	**0.310**	*0.009*	**0.351**	*0.010*
	Duration	**0.414**	*< 0.001*	**0.515**	*0.019*	**0.394**	*0.002*
	Status	**-0.243**	*0.006*	**-0.243**	*0.008*	**-0.206**	*0.016*
	Locations					0.163	*0.133*
	Female					0.239	*0.051*
Time	Time			-0.166	*0.230*		
	ΔGBC^2 # time			0.060	*0.293*		
Intercept adjustments by phase	Design					**-0.307**	*< 0.001*
	Prototype					0.230	*0.078*
	Pilot					**0.487**	*0.001*
	Implement						
Slope adjustments by phase	Design # AWVCI					**-0.505**	*0.010*
	Prototype # AWVCI					**-0.431**	*0.002*
	Pilot # AWVCI					**-0.734**	*0.000*
	Implement # AWVCI						
	Constant	3.613	*< 0.001*	3.621	*< 0.001*	2.186	*0.044*
Model fit and summary statistics	Model F test						
	Model chi2 test	35.68	*< 0.001*	41.49	*< 0.001*		
	Root Mean Square Error	3.415		3.473		2.799	
	rho	0.467**		0.482**		0.000	
	log likelihood					-0.019	
	aic					468.3	
	bic					493.2	
Random Effects	sd_Ui					1.425	
	SE(sd_Ui)					0.398	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

One-tailed p-values are reported.

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 18: Results from testing Hypotheses 5a and 5b

Figure 24 displays results graphically with linear regression models for each team and each innovation process phase.

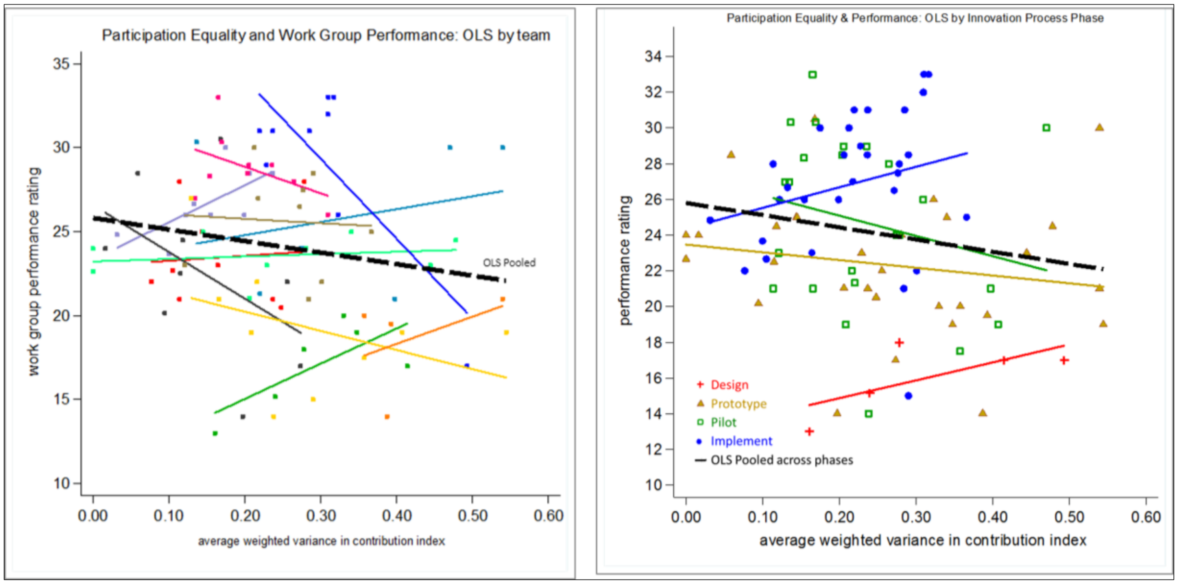


Figure 24: Graphical display of results from testing Hypotheses 5a and 5b

Hypothesis 5b, for which we found partial support, supposed that innovation process phase would moderate the negative association between AWVCI and performance ratings. Table 18 displays Model 6 with intercept and slope adjustments by phase and background variables for network actors, project duration, status equality, locations per team member, and gender distribution.

Contrary to expectations, we observed a positive and significant association between AWVCI and performance in the implementation phase base level ($\beta = 0.518, p = 0.001$). For every one-SD increase in AWVCI, we expect just over a ½-SD increase in performance ratings (just over 2.5 points on a 28-point scale and 12.7% of the observed range of the performance rating variable). Results in the other three phases offer support of Hypothesis 5b: ($\beta_{design} = 0.518 -$

$0.768, p < 0.002)$, ($\beta_{prototype} = 0.518 - 0.597, p = 0.05)$, and ($\beta_{pilot} = 0.518 - 0.824, p = 0.001)$. During pilot phase, we expect a 3/10th-SD decrease in performance ratings (about 1.5 points on a 28-point scale and 7.5% of the observed range for the performance rating variable) for a one-SD increase in AWVCI.

5.4.6 Participation Equality and Radical Innovation

Hypothesis 6a predicted a positive relationship between participation equality and radical innovation, represented by a negative association between AWVCI and innovation ratings. Table 19 displays model results in which we find no support of the hypothesized relationship. The relationship between AWVCI and innovation is weakly negative in Model 4 ($\beta = -0.041, p = 0.26)$ and weakly positive in Model 5 alongside time ($\beta = 0.011, p = 0.46)$. The interaction between AWVCI and time in Model 5 was weakly negative and not significant ($\beta = -0.061, p = 0.32)$. Figure 25 displays results graphically with linear regression models for each team and each innovation process phase.

Hypothesis 6b, for which we found limited support with Model 6 (controlling for tenure diversity, project duration, and team member locations as shown in Table 19), stated that innovation process phase would moderate the negative relationship between AWVCI and innovation ratings. We observed a mild version of the hypothesized negative relationship during implementation phase ($\beta = -0.155, p = 0.03)$; here we expect a 0.16-SD decrease in innovation (about 7.5 points on a 300-point scale and 3% of the observed range for the innovation rating variable) for a one-SD increase in AWVCI.

Dependent Variable	INNOVATION	4. Panel-corrected standard errors		5. PCSE with time		6. Mixed effects with phases	
Independent Variables	AWVCI	-0.041	*0.257*	0.011	*0.458*	**-0.155**	*0.028*
	Tenure	0.095	*0.073*	0.096	*0.070*	0.081	*0.067*
	Status	0.094	*0.082*	0.092	*0.096*		
	Density	**-0.151**	*0.007*	**-0.164**	*0.004*		
	Actors						
	Duration					0.109	*0.193*
	Locations					**0.164**	*0.017*
Time	Time			0.032	*0.397*		
	AWVCI # time			-0.061	*0.321*		
Intercept adjustments by phase	Design					**-0.413**	*< 0.001*
	Prototype					**-0.251**	*0.001*
	Pilot					**-0.494**	*0.001*
	Implement						
Slope adjustments by phase	Design # AWVCI					**0.302**	*< 0.001*
	Prototype # AWVCI					**0.165**	*0.013*
	Pilot # AWVCI					**0.414**	*0.002*
	Implement # AWVCI						
	Constant	5.121	*< 0.001*	5.129	*< 0.001*	5.115	*< 0.001*
Model fit and summary statistics	Model F test						
	Model chi2 test	10.44	*0.034*	14.07	*0.029*	95,800,000	*< 0.001*
	Root Mean Square Error	25.47		21.30		21.30	
	rho	0.578**		0.580**		0.262	
	log likelihood					-411.7	
	aic					843.4	
	bic					868.3	
Random Effects	sd_Ui					39.45	
	SE(sd_Ui)					11.62	

n = 89

Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).

One-tailed p-values are reported.

** Panel-specific Autocorrelation; average team AR(1) displayed

Table 19: Results from testing Hypotheses 6a and 6b

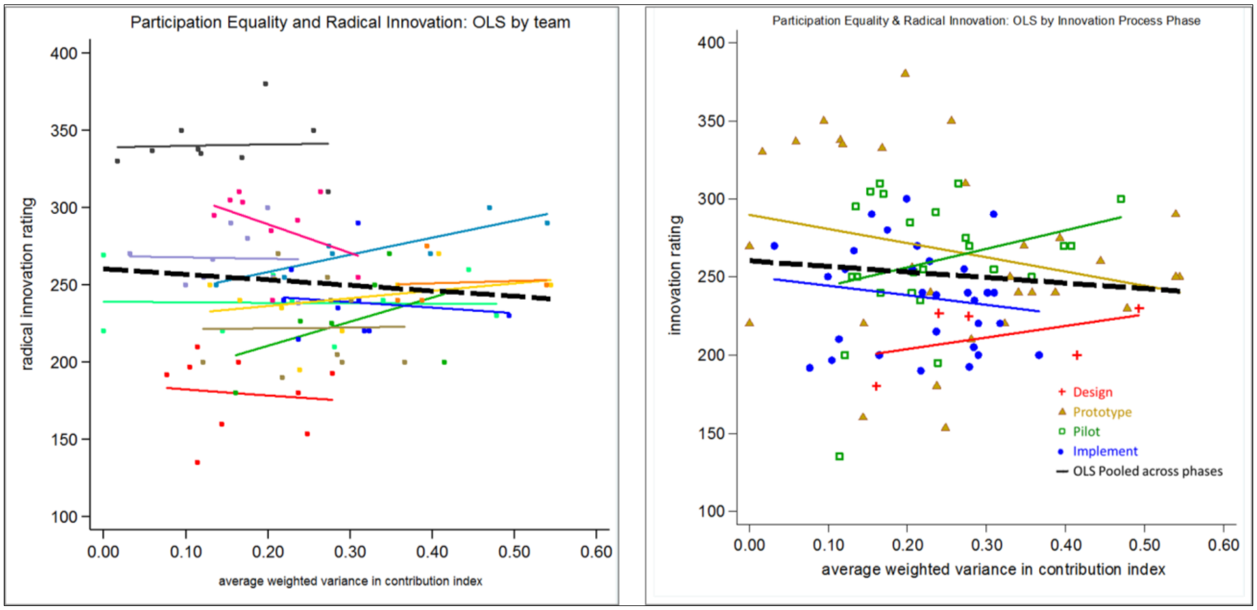


Figure 25: Graphical display of results from testing Hypotheses 6a and 6b

We observed significant slope adjustments during design, prototype, and pilot phase that resulted in positive associations counter to our hypothesis, the most noteworthy of which appears during pilot phase ($\beta = -0.155 + 0.414, p = 0.002$), where we anticipate a ¼-SD innovation increase (just over 12 points on a 300-point rating scale and 4.9% of the observed range of the innovation rating variable) for a one-SD increase in AWVCI.

Hypothesis	IV	directionality	DV	moderator	Supported?	β	β Design	β Prototype	β Pilot	β Implement
1a	GBC	negative	Performance		no	**0.296**				
1b	GBC	negative	Performance	PHASE	partial		-0.068	**0.064**	0.364	**0.374**
2a	GBC	negative	Innovation		no	**0.202**				
2b	GBC	negative	Innovation	PHASE	partial		**0.150**	-0.028	0.075	-0.218
3a	GBCsq	positive	Performance		no	0.038				
3b	GBCsq	positive	Performance	PHASE	partial		**-0.257**	0.053	**-0.140**	0.210
4a	GBCsq	positive	Innovation		yes	0.194				
4b	GBCsq	positive	Innovation	PHASE	partial		0.694	0.241	0.682	0.290
5a	AWVCI	negative	Performance		no	-0.015				
5b	AWVCI	negative	Performance	PHASE	partial		-0.250	-0.079	-0.306	**0.518**
6a	AWVCI	negative	Innovation		no	-0.041				
6b	AWVCI	negative	Innovation	PHASE	partial		**0.147**	**0.011**	**0.260**	-0.155
Green indicates support for hypothesis				Standardized beta coefficients (bolded to indicate statistical significance at α = 0.05).						

Table 20: Summary of results for Hypotheses 1a – 6a and 1b – 6b

5.5 Results Summary

This chapter has described our panel dataset structure and discussed findings from diagnostic testing and subsequent implications for model selection. We specified the models used to test hypotheses, panel-corrected standard errors and random intercept models. The final section shared estimation model results (summarized in Table 15) and accompanying graphics for each hypothesis tested.

The next chapter will discuss implications of these findings and revisit our theorization as described in Chapter 3. We consider limitations to the generalizability of our results, identify interesting research questions for future studies of virtual innovation teams, and recognize contributions of this study to both theory and practice.

CHAPTER 6. DISCUSSION

How do the collaborative structures of virtual teams change over time and to what extent do these dynamics impact innovation processes and performance? Our research question emerged from the growing yet still fallow intersection of research on virtual teams and scholarly consideration of group-level innovation.

We considered team centrality, structural dynamics, and participation equality as potential drivers of two virtual innovation team outcomes, work group performance and radical innovation. We also considered how these relationships might vary as a function of the innovation phase in which teams were operating. Our results offer partial support for the six hypotheses tested. Contrary to what we predicted, team centrality was positively associated with performance and innovation. As expected, higher levels of structural dynamics were positively associated with innovation and higher levels of participation equality were positively associated with performance. We observed interesting variation in these relationships across four innovation process phases.

6.1. Network Centrality in Virtual Innovation Teams

Centralization in a network describes the extent to which interactions and flows of information are concentrated around a small number of team members or distributed correspondingly among collaborators. Measures of group-level centrality quantify variance in individual centrality of group members (Sparrowe et al. 2001). High levels of team centrality represent a star-like network structure with a central hub whereas lower levels of team centrality characterize networks with developed peripheral connections and comparable levels of connectivity amongst team members (Borgatti 2005).

6.1.1 Discussion of Team Centrality Results

We predicted a negative association between team centrality and virtual innovation team outcomes, reasoning that the virtual nature of collaboration was well-suited to a distributed, decentralized team structure. We also considered that idea generation and evaluation (activities associated with innovation in groups) would benefit from a democratic team structure in which team members were connected without a central intermediary. Contrary to expectations, we observed a positive association between team centrality and performance as well as a positive association between team centrality and radical innovation. In other words, innovation team outcomes were enhanced when team communication networks had one or a few central individuals serving as a hub for the flow of information amongst team members.

The positive and significant association between team performance and radical innovation was observed when controlling for the effects of time. We also found an interesting effect with the interaction between team centrality and time; as time passed, the association between GBC and innovation decreased. This result suggests that the negative impact of team centralization may be accentuated over time, whereas collaborative innovation benefits from a highly central team member earlier in the team lifespan.

Optimal team structures minimize the need for coordination (Macmillan et al. 2004), and we reasoned that communication networks with a central individual mediating information flows would increase the need for coordination. But it may be that the presence of central team members with certain capabilities benefit virtual innovation teams, outweighing coordination costs associated with a communication hub. Central individuals benefit from information exchange with respect to timing, access, and referral and thus can serve as knowledge brokers (Burt 1992) in their respective groups. In Chapter 2 we discussed information elaboration, the sharing of team member information resources in ways that generate new knowledge and actionable solutions (Resick et al. 2014; Van Knippenberg et al. 2004). An individual situated at the center of the team communication network likely has insight with respect to expertise location, a sort of meta understanding of who on the team knows what (Faraj and Sproull 2000). Thus the central team member would be well-positioned to shepherd information elaboration processes on the team.

Multiple studies have found centrality of an individual to be positively associated with individual performance (Ibarra 1993; Sparrowe et al. 2001) and other key processes such as knowledge sharing (Thomas-Hunt et al. 2003). High frequency of communication was positively linked to individual performance in a study of virtual teams, and centrally-situated team members are positioned to interact with more frequency and intensity (Sarker et al. 2011). Groups in which the central individual had generalized knowledge about the focal task out-performed groups in which the central individual had specialized knowledge in an experimental study (Rulke and Galaskiewicz 2000). The performance-enhancing benefits of a central knowledge network position may be moderated by absorptive capacity (Cohen and Levinthal 1990) of the central unit (Tsai 2001), the extent to which they can identify and integrate relevant knowledge that the team needs to execute (Tortoriello et al. 2012). Research on multimodal networks (incorporating dyadic interactions amongst human users and technological units as equivalent nodes) indicates that the centrality of information systems within a network is associated with efficiency and quality of group-level outcomes (Kane and Alavi 2008). The results summarized in this paragraph all point to characterization of the central individual (as well as resources and/or capabilities that they may contribute) as essential elements in understanding how individual-level centrality may influence team-level outcomes.

A study of health care teams working with an electronic medical record system suggested that group performance was impacted by the average level of system proficiency – no surprises there. But more predictive of team success was centrality-proficiency alignment, the extent to which central team members had high proficiency (Kane and Borgatti 2011). These results suggest that optimal team performance may be achieved when members with relevant skills are centrally located and positioned to support others. If team-level performance is a function of the individual-level effectiveness of highly central team members, it may be that our results reflect variation between the virtual innovation teams that we observed with respect to the presence of effectual knowledge brokers as well as some sort of process for their timely emergence as central in the team communication network.

6.1.2 Team Centrality Results over Innovation Process Phases

Overall, innovation and performance outcomes were both positively associated with team centrality. Both of these relationships were moderated significantly by innovation process phases, but the pattern of variation across phases differed with each outcome. Our results for innovation team performance hint at the hypothesized negative association between team centrality and performance in a team’s initial design phase, although we have limited insight into the design phase because our models draw on relatively few observations of teams in the earliest stage of the innovation process. We observed the strongest positive association between team centrality and performance during pilot testing and implementation, the third and last of the four phases. Advanced testing and implementation (the hardwiring of a successful innovation into targeted systems) bring a new set of challenges for innovators (Hargadon and Douglas 2001), but team success in implementing innovations seems more contingent on effective execution. The need for efficient coordination of virtual team members for high achievement in later innovation phases could be met with centralized team structures.

Looking across innovation process phases at the relationship between team centrality and radical innovation, we saw an opposite sequencing to that observed with performance ratings. In the models with innovation as a response variable, team centrality was positively associated during design phase and pilot phase. We observed the hypothesized negative association during the final implementation phase, suggesting that a decentralized structure for team communication is most beneficial once the focal innovation has been developed and the team is focusing on hardwiring that innovation into targeted systems. The benefits of a more peripheral orientation for teams in later phases may reflect the need for more external communication as teams test innovations in a broader range of contexts and seek feedback from a broader range of stakeholders (Baer 2012). Whereas communication in earlier generative and testing phases seems likely to be oriented internally; at this point development of the innovation is occurring in a more abstract sense via iterative discussion amongst team members or with local testing of innovative ideas in prototype forms. The tolerance of risk and ambiguity required for innovation success is much more potent in earlier phases of product development (Eisenhardt and Tabrizi 1995), suggesting the need for more centralized structures to keep information flowing amongst team members in the face of uncertainty (Buijs 2007).

6.2 Structural Dynamics in Virtual Innovation Teams

The previous section described evidence from research connecting characteristics of individual team members in central network positions with team-level performance. The capacity of centrally positioned team members to thrive as the general knowledge broker is well-recognized as a key driver of team effectiveness amongst network researchers It seems clear that shifting demands of the innovation process would lead to fluctuation with respect to which team members had the most relevant and valuable knowledge resources (Perry-Smith and Shalley 2003).

These insights are relevant to our examination of team centrality, but also insightful in exploring how changes in the levels of team centrality over time (structural dynamics) impact innovation team outcomes. We hypothesized that regular variability in communication patterns could represent the fluidity and agility associated with successful virtual innovation teams (Sarker and Sarker 2009). Frequent and/or sizeable changes in levels of team centrality (i.e., high structural dynamics) could be a signal of effective collaboration in a dynamic work environment characterized by uncertainty. Classic organizational research distinguishes between predictable workplace situations in which routine processes are sufficient for action (Galbraith 1973) and uncertain conditions that call for flexibility and improvisation (Scott 1987) to compensate for a lack of guidance from previous experience. The following quote is illustrative in understating the turbulence that can characterize innovation work:

> Product development is a very uncertain path through foggy and shifting markets and technologies. Thus acceleration in this scenario involves rapidly building intuition and flexible options so as to cope with an unclear and changing environment. Yet, simultaneously, it also involves providing enough structure so that people will create sensemaking, avoid procrastination, and be confident enough to act in these highly uncertain situations, which easily lead to paralyzing anxiety and conflict. This approach is thus more a response to uncertainty than certainty, more iterative than linear, and more experienced-based than planned (Eisenhardt and Tabrizi 1995: 88).

Shifts in the level of team centrality may signal dynamics in which teams converge around a leader (high centrality), and then disperse to carry out individual tasks or seek external sources of knowledge (low centrality). Such oscillations in centrality may also be indicative of shared leadership behaviors (Carson et al. 2007; Pearce et al. 2004) and effective integration of knowledge resources from each team member (Kanawattanachai and Yoo 2007).

6.2.1 Discussion of Structural Dynamics Results

Contrary to what we expected, structural dynamics was not associated with team performance overall. We found evidence for the performance-enhancing effects of structural dynamism that we predicted when the outcome of interest was radical innovation and when time was incorporated into our model. Overall, we observed that greater fluctuation in the level of team centrality was associated with higher innovation ratings. When examining how this result varies across innovation process phases, we observed that the positive relationship was strongest during design and pilot phases. This result is consistent with our observation of how the interaction between structural dynamics and time impacted radical innovation. As time increases, the positive association between changes in levels of centrality and innovation ratings decreases slightly. These results suggest that structural dynamics may be of greatest benefit during earlier phases of innovation team lifespan.

6.2.2 Structural Dynamics Results over Innovation Process Phases

Returning to our assessment of structural dynamics and performance, we also considered how a relationship between shifting centrality structures and team effectiveness might vary across innovation phases. It is reasonable to assume variation across phases with respect to optimal levels of structural dynamism given the variation in cognitive demands and coordination challenges in each innovation phase.

We observed the hypothesized positive impact of structural dynamics on performance during prototype and implementation phases and a negative association during design and pilot phases. We did anticipate that the need for and benefits derived from high levels of structural dynamics would attenuate over phases, but still predicted a positive association. One explanation for this non-sequential pattern of variation across phases is the "continuous alternation of the generative and the focusing" modes of innovation in teams (Buijs 2007: 204). Team member interactions throughout the innovation process are based around four main activities: exchanging information, learning, motivating, and negotiating (Drach-Zahavy and Somech 2001). These activities are likely to occur during each phase to a certain extent. If team centrality structures that optimize information exchange differ from those that facilitate negotiations amongst team members in defining and developing an idea, structural dynamics could impact team outcomes variably even within each phase.

Our observation of structural dynamics and radical innovation across phases revealed a positive association during each phase, but significantly stronger during design and pilot testing (the first and third phases observed in this study). The intervals in which structural dynamics may strongly impact performance could overlap with periods of learning, reflection, and negotiation of shared design frames that help to crystallize the innovation process and provide direction for next steps in testing and development (Hey et al. 2007). We observed a relatively strong positive effect of high dynamism during pilot phase followed by a weaker positive association during the final implementation phase. Diminishing returns to structural dynamics may occur during the end of an innovation project given that teams have settled into structural patterns (as a result of time spent collaborating) which are optimal for the idiosyncratic inputs, goals, and emergent interactions of the team. In other words, there is less need for exploratory shifts in team structure after teams gain experience working together.

6.3 Participation Equality in Virtual Innovation Teams

When a team relies primarily on technology for interaction, to participate is to communicate with other team members. Thus examination of the communication network is useful in understanding how contributions are distributed across team members. In this study, we conceptualize participation equality on a virtual innovation team as an indicator of evenly distributed task activities and comparable levels of initiative amongst team members as evidenced by balanced communication behaviors.

6.3.1 Discussion of Participation Equality results

Overall, irrespective of innovation process phase, we observed little to no association between participation equality and both innovation team outcomes. Previous research offers divergent evidence on the impact of equal participation; for example, it had a negative impact on team performance alongside expertise diversity (Martins et al. 2012). Other studies suggest that participation equality is essential (Pentland 2012), particularly for virtual teams (Weisband et al. 1993) and innovation teams in which idea generation and development depends on the open exchange of dialogue (Drach-Zahavy and Somech 2001). Inclusion of minority opinions has been long associated with increased generation of novel solutions (Nemeth 1986). Research offers much evidence that virtual communication neutralizes the impact of status and influence such that participation of team members is commensurate. But other studies suggest that virtual teams reconstruct status differences based on social cues such that participation patterns resemble that of face to face teams (Weisband et al. 1993)

We were surprised to see no direct effects of participation equality on virtual innovation team outcomes, but we did observe some interesting variation across innovation process phases.

6.3.2 Participation Equality Results over Innovation Process Phases

As predicted, participation equality benefitted team performance in the earlier innovation process phases with the strongest effect observed during pilot testing. Contrary to expectations, participation equality was negatively associated with performance during the final implementation phase. In fact, we anticipated that the positive association would decline over the four phases, but did not expect the positive relationship to change directionality. It may be that implementation phase is "too late" for participation equality in the sense that team members' contributions should be well-defined by that point and not necessarily commensurate in size and scope. So higher variation in communication behaviors across team members could reflect that team members are working effectively on the tasks to which they are best suited.

We observed a different pattern across phases when testing for the relationship between participation equality and radical innovation. Opposite from our results with team performance, we observed the hypothesized positive relationship during implementation phase with a weak negative relationship during earlier phases. It seems counterintuitive for the strongest association between participation equality and innovation to appear towards the end of the innovation process. And yet there remains "enormous interdependence among experts in projects of any meaningful scope" (Edmondson and Nembhard 2009: 124; Galbraith and Kazanjian 1988). Diverse sources of information from cross-functional team members expands the range of possibilities for innovation in every phase, and it may be that equal levels of participation during implementation phase are useful for teams in synthesizing feedback from application of their idea in various contexts. Thus the need to integrate diverse information may not be limited to generative phases when innovation is the focal outcome.

This integration can occur when team members exhibit behaviors of *inquiry* (Garvin and Roberto 2001), explaining their ideas and asking questions about perspectives of others such that any potential conflict can be put to creative use. Prevalent is the "task force" model for innovation teams in which team members are selected based on particular specialized knowledge. There is a need for mechanisms to counterbalance lack of group longevity, which has been shown to moderate diversity and task conflict with performance (Pelled et al. 1999; Schippers et al. 2003). Fluid innovation teams may take on new members as an idea moves towards implementation, a possible explanation for a resurgence of participation equality during late phases of innovation.

Open channels of communication and even distribution of dialogue seem overall to be positive for virtual innovation teams (Cordery and Soo 2008; De Dreu and West 2001), but the nature of innovation and virtual work suggests periodicity in individual contributions. Members of virtual innovation initiatives may be volunteers who work full time elsewhere but contribute to a team when possible in an asynchronous fashion. Virtual innovation teams need collaborative structures that capitalize on, or at least accommodate, porous team boundaries and fluid membership in innovation teams (Edmondson 2012).

6.4 Discussion Summary

In this chapter we reflected on results presented in the previous chapter from our longitudinal study of communication network dynamics exhibited by eleven virtual health care innovation teams. We revisited our theory development with new insights from results of testing six hypotheses concerning how virtual innovation team processes and outcomes might be constrained or enabled by variation in levels of team centrality, structural dynamics, and participation equality. We also considered how these relationships might vary as a function of the innovation phase in which teams were operating. Our results offer partial support for the six hypotheses tested. Contrary to what we predicted, team centrality was positively associated with performance and innovation. As expected, higher levels of structural dynamics were positively associated with innovation and higher levels of participation equality were positively associated with performance. We observed interesting variation in these relationships across four innovation process phases.

The following chapter will conclude this dissertation. Here will we discuss limitations to the generalizability of conclusions that we can draw from our results and consider interesting avenues for future research. We contemplate the rigor and relevance of this dissertation study and identify contributions to research and practice.

CHAPTER 7: IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

The previous chapter discussed implications of our results and revisited our theoretical model in light of new insights about virtual innovation team collaboration dynamics. This chapter will conclude the dissertation. Here we consider limitations to the generalizability of conclusions that we can draw based on study results. We propose interesting avenues for future research. We identify contributions to this study. In a practical sense, our findings could inform the design and management of future virtual innovation teams and the ecosystems in which they are embedded. Our methodology is innovative and could serve as a guide for other longitudinal studies drawing on communication networks generated by digital exhaust. This research also affords opportunities for new theory development, as do most studies drawing on data sources and methods which are outside of the dominant methodological paradigm in a research domain. We contribute to theories about collaboration in virtual innovation teams and more generally to understanding of virtual team performance.

7.1 Summary of Insights from Results

So far in this dissertation we have proposed a research question about collaboration dynamics in virtual innovation teams and outlined a longitudinal, network-based approach to investigating that question. We considered team centrality, structural dynamics, and participation equality as theoretical drivers of virtual innovation team processes and outcomes. We also explored how these main effects might vary as a function of the innovation process phase in which teams were operating.

We found limited support for the six hypotheses tested. Contrary to what we predicted, team centrality was positively associated with performance and innovation. As hypothesized, participation equality was positively associated with virtual innovation team performance and structural dynamics was positively associated with radical innovation. We observed interesting variation in these relationships across four innovation process phases.

7.1.1 Summary of Insights on Team Centrality

We anticipated a negative association between team centrality and team effectiveness, reasoning that the very nature of virtual collaboration seemed to resonate with a distributed, decentralized work flow. We also supposed that open lines of communication (as reflected by a low centrality email network) would cultivate a democratic team culture based on self-organization around relevant resources rather than the traditional command and control approach. And yet our hypotheses about team centrality revealed a positive association. While counter to what we expected, it is interesting to consider how and when centralized structures may be conducive to a virtual and/or innovation work context (Nemoto et al. 2011; Sparrowe et al. 2001; Tsai 2001).

We also observed that the association between team centrality and innovation decreased as time progressed. This result suggests that the negative impact of team centralization may be accentuated over time, whereas collaborative innovation benefits from a highly central team member earlier in the team lifespan.

Both of the positive relationships between team centrality and team outcomes were moderated significantly by innovation process phases, but the pattern of variation across phases differed for performance as compared to radical innovation. The increased need for efficient coordination of virtual team members in later innovation phases could be met with centralized team structures.

Looking across innovation process phases at the relationship between team centrality and radical innovation, we saw an opposite sequencing of phase moderating effects to that observed with performance ratings. With radical innovation as the response variable, team centrality was beneficial during the first design phase and third pilot phase. We observed the hypothesized negative association during the final implementation phase, suggesting that decentralized communication is conducive to managing team members as they try to establish an innovation within the targeted system.

7.1.2 Summary of Insights on Structural Dynamics

In addition to examining levels of team centrality, we also explored how the intensity of *change* in team communication network structures may support or hinder team functioning. We predicted that variability in communication patterns (represented by fluctuating levels of team centrality) could exemplify the ambidexterity associated with successful virtual innovation teams (Bledow et al. 2009; Sarker and Sarker 2009). Volatility with respect to team centrality (i.e., high structural dynamics) could be a signal of innovation team effectiveness in a dynamic work environment characterized by ambiguity.

We found evidence for the performance-enhancing effects of structural dynamism that we predicted when the outcome of interest was radical innovation and when time was incorporated into our model. Looking across innovation process phases, we observed that the positive relationship was strongest during design and pilot phases. This result suggests that frequently shifting communication network structures may be most potent for teams engaged in idea generating and testing, relative to implementation and spread of an innovation.

Structural dynamics was not significantly associated with performance when tested as a main effect. We observed a relatively strong positive association between structural dynamics and performance during prototype testing and a weaker positive association during the final implementation phase. This observation points to the possibility of diminishing returns to structural dynamics as teams evolve and members gain experience working together (Gersick 1988, 1989). Team structures could move asymptotically towards a level of centrality that is optimal for a particular team based on their resources, aims, and other contextual factors such as the extent of virtualness and diversity of team members.

7.1.3 Summary of Insights on Participation Equality

Team communication networks are helpful in understanding how tasks and contributions are distributed across team members. When a team relies on technology for interactions, communication and participation are often one and the same. Neither performance nor innovation exhibited much of an association with participation equality in this study, although we anticipated a positive association. Our theoretical rationale suggested that participation equality was a signal for effectiveness in the form of evenly distributed work tasks to match team resources as well as comparable levels of initiative (i.e., everybody speaking up). The latter aspect could be particularly important for innovation teams working to generate and evaluate ideas.

We observed some participation equality effects across innovation process phases. As predicted, participation equality benefitted team performance in the earlier innovation process phases and least so during implementation phase. Perhaps implementation work (or any work later in a team's lifespan) does not gain as much from participation equality because team members have recognized and settled into work patterns based on their capabilities. These patterns are not likely to be comparable in scope and to require similar associated communication behaviors. While participation equality may not distinguish thriving virtual innovation teams in later phases, it could be an essential ingredient in early success.

Again, we found a different pattern across phases when testing for the relationship between participation equality and radical innovation (relative to what we observed with performance as the focal outcome). Participation equality exhibited our proposed positive effects during implementation and weak negative associations during earlier phases. Participation equality could be important for a team during implementation as it is for generativity of ideas if team members need to integrate feedback from diverse users or are attempting to pool their learning from application of the innovation in different contexts.

7.2 Limitations to Generalizability

Here we consider limitations to the generalizability of conclusions based on our study results. Other vulnerabilities of this research are considered in the following section on future research opportunities. Generalizability, also commonly known as external validity, is the extent to which conclusions drawn from study results may be attributed to other individuals and other situations

(Cook and Campbell 1979). Generalization of our results to other virtual teams and innovation teams in other contexts is limited by several factors (McGrath 1982).

The eleven virtual innovation teams observed in this study were all connected as part of a large-scale health care system design project. Thus our team study is similar to others in which all teams observed are from the same organization. Results that emerge from within a single organization face clear limits to external validity, or generalizability to other populations and contexts (Cook and Campbell 1976). One silver lining of our teams operating under the auspices of a single institution was the built-in control for cultural and administrative variables such as climate for innovation and organizational culture that may explain variation in creativity and innovation outcomes (Baer and Frese 2003; Burningham and West 1995; Tesluk et al. 1997).

Multiple elements of our study context differed from the environments in which many virtual innovation teams work. One distinguishing feature of the project observed in this study was the relative novelty of innovation work and multidisciplinary collaboration to many team members. Most teams involved in the C3N Project engaged end users such as patients and their families in co-design. Project leaders also mindfully recruited multidisciplinary researchers and practitioners from outside the medical field. Many intrinsically motivated team members were unpaid and contributed asynchronously.

Our study of self-organizing innovation teams with unconventional participants driven by entrepreneurial and prosocial motivations is highly relevant to a smaller group of initiatives that fall within this 'grassroots' niche of the innovation enterprise. Many cutting edge virtual collaborations similar to the C3N Project are emerging in collaborative networks and other new digitally enabled organizational forms. Our focal teams shared many characteristics with these increasingly common work groups representing the future of collaboration and meriting scholarly attention. Still, key differences remain between our sample and other enduring virtual teams that consist entirely of paid professionals contributing in the course of their regular job responsibilities. While the digital economy continues to transform the ways we work, canonical team structures still dominate the modern innovation enterprise and also shape prevailing scholarly conceptualizations of virtual and innovation teams in the management and organization science literatures.

Many variables that could impact the processes and performance of virtual innovation teams were not examined in this study, and thus represent plausible alternative theoretical explanations for our observed variation in innovation team outcomes. Despite these limitations, this dissertation offered a compelling line of inquiry into our research question. Generalizability of our findings is limited, but this study offers thought-provoking insights for virtual teams and innovation teams across all contexts. Our results and limitations both point to multiple opportunities for further team research around virtualness, innovation, and team development over time.

7.3 Future Research Opportunities

How do the collaborative structures of virtual teams change over time and to what extent do these dynamics impact innovation processes and performance? Findings from this study (and, in some cases, the absence of findings) suggest new theoretical insights around this research question. Our conclusions also point to new research questions and suggest some potential priorities for researchers seeking to contribute to what is known about performance of virtual teams and innovation teams. This particular study could also be extended in multiple ways to address some of the weaker links in our study design.

One shortcoming of our email-based network strategy is the potential sensitivity of results to variation in modeling assumptions both network-based and statistical. Of course, all studies require methodological choices that limit conclusions that might be drawn from results (McGrath et al. 1982). But a few design choices in this particular study merit consideration in the prioritization of future research drawing on digital network data. For example, we chose keywords to identify team-specific email amongst all the messages collected. Our efforts to validate the keywords (including sensitivity analysis by singly adding and removing terms) were reassuring. But we cannot test keywords that have not been identified, and use of some missing terms might tap into team correspondence that is not currently incorporated in our analysis. It is likely that using keywords fails to capture all relevant communication flows. Deficiency in capturing team interactions, however, seems preferable to contamination that could result from filtering messages by time periods and team members only. Our multiple filter approach (keywords and actors) offers confidence that the messages that do appear in our team-specific network models are in fact relevant to the team. Overlapping team membership was the impetus for our relatively exclusive approach to identifying team-specific messages. Because many study participants were involved in multiple teams in our sample, we needed a method to filter within individual mailboxes. Other email-based network studies observing teams with no overlapping membership might consider casting a wider net or including all team member messages in email network models.

We were surprised to observe in this study that team centrality seemed to benefit team outcomes. We could perhaps explain some of these results with a more granular examination of the particular individual team collaborators exhibiting high actor centrality. It would be interesting to see if central collaborators are typically a designated team leader, and also useful for theoretical consideration of the role of central actors in shepherding information elaboration and other knowledge integration processes. Characterization of the central individual (as well as their resources and/or capabilities) is important in understanding how individual-level centrality may influence team-level outcomes (Kane and Borgatti 2011; Thomas-Hunt et al. 2003).

If a central position seems to be a structural fixture in virtual team communication networks, it is interesting to consider the extent to which the inhabitant of that position endures or changes. Perhaps high centrality rotates among high-functioning team members; one member shifts to a central position when his or her idiosyncratic expertise or experience is best suited to guide team knowledge transfer in ways that lead to action. Our examination of structural dynamics in this study was intended to shed light on how changes in centrality, not merely the levels of centrality, may influence team functioning. Future studies could support this line of inquiry with development and validation of our structural dynamics measure, the average squared distance between weekly observations of team centrality. It could be enlightening to statistically control for the count of oscillations in team centrality when using the magnitude of changes in centrality as a predictor (as did this study).

Our email-based network data (or other observations of digital exhaust from virtual interactions) could be a fascinating foundation to inform stochastic actor-oriented models that are increasingly prevalent in network research across disciplines (Burk et al. 2007; Snijders 2005; Van de Bunt and Groenewegen 2007). Building on prescribed inputs and simple rules that simulate thousands of interactions, actor-oriented and the conceptually similar agent-based models are capable of transcending some practical limitations to what researchers can learn from the range of sample sizes afforded by traditional field study designs (Bonabeau 2002; Epstein 1999; Kiesling et al. 2012; Wilensky and Rand 2015). These network-based simulation models could complement research questions about how desirable network effects might emerge in collaborative innovation initiatives as a function of design, governance, incentive structures, and other inputs of interest to the practitioner (Levine and Prietula 2013). The use of empirical network observations such as those in this study to ground assumptions underlying an agent-based or actor-oriented simulations would make for a compelling study design to further investigate how individual and team behaviors both generate and respond to the networks in which they are embedded.

A major assumption of this work is that email correspondence reflects a team's general communication patterns. While email has become a first-order means of communication for teams both virtual and co-located (Sproull 1991; Wellman 2001), email alone may not provide a comprehensive representation of team interaction structures (Grippa et al. 2006; Johnson et al. 2012). Researchers have discovered compelling evidence of congruence between e-mail-based and other representations of communication networks (Bulkley and Van Alstyne 2006; Ebel et al. 2002; Gloor et al. 2003; Tyler and Tang 2003). Yet an optimal network study design might incorporate multiple modes of communication, including chat, telephone, social media, written correspondence, and face-to-face interaction (Grippa 2009). The research question – and the extent to which its focal phenomena are best suited to observation in a socially-constructed or digital trace network – serves as a useful guide in selecting a survey-based or digital trace approach to data collection for SNA (Crowston et al. 2010; Quintane and Kleinbaum 2011).

The literatures on virtual teams and team innovation currently feature multiple streams of research that could be strengthened with future studies incorporating a network-based framework. Network heterogeneity (Lawrence 1997) is a construct that could aptly combine some of the diversity-oriented background variables in our study, capturing the gestalt effect of relevant social, structural, and cognitive categorizations (Reagans and Zuckerman 2001). Average tie strength is another potentially informative network measure of interpersonal relationship strength (Granovetter 1973) and frequency of interaction amongst team members (McFadyen et al. 2009). Intergroup conflict is a key variable in the behavioral dynamics of networked groups (Labianca et al. 1998) that was not explicitly considered in this study.

Innovation teams are likely to experience both inter-team conflict (Pirola-Merlo et al. 2002) and collective excitement associated with creative endeavors (Amabile et al. 2005), and both positive and negative affective work experiences can benefit work groups (Bartel and Saavedra 2000; George and Zhou 2007). Thus future research on virtual innovation teams could benefit from examination of both conflict and emotional regulation in shaping team dynamics. Leveraging conflict to integrate divergent opinions is a well-recognized antecedent to team-level innovation (Chen 2006; Miron-Spektor et al. 2011b). Enhanced understanding of whether and how centrality structure and participation dynamics might enable teams to leverage constructive conflict would be a strong contribution to the virtual and innovation team literatures (Martins et al. 2012; Miron-Spektor et al. 2011b). We recommend future research on how network structures and communication patterns may constrain or enable virtual collaborations with respect to the generativity of interactions amongst participants (Faraj et al. 2011), the management of interpersonal dynamics (Carmeli et al. 2009; Perry-Smith 2006), the development of trust (Jarvenpaa and Leidner 1999; Paul and McDaniel 2004), and other elements of enacting collaborative conditions from which innovative ideas are more likely to materialize.

Emotionality, a powerful cognitive filter impacting all social and work interactions (Barsade and Gibson 1998), is a compelling research stream for organizational scholars (Elfenbein 2007; Maitlis et al. 2013). This study has examined the structure of team network ties and how that structure changes. What then might we learn from studying the *content* of the information flows that traverse these network ties? Interesting questions abound with respect to the social, emotional, and cognitive signals lurking in the content of our email messages. Consideration of this content alongside observed network structures could be groundbreaking for theories of knowledge integration in virtual teams through direct observation of team knowledge flows.

The work environment for innovation-seeking initiatives and new product development teams is likely to be dynamic, demanding, and characterized by uncertainty (Edmondson and Nembhard 2009; Markus et al. 2002). Examination of emotionality in team communication (and/or extent of variation in individual team members' emotionality) alongside structural team variables such as centrality could be fruitful. Dual consideration of structure and content in studying team information flows could lead to new insights about the role of emotional intelligence for teams in developing successful mechanisms for coordination and knowledge integration (Woolley et al. 2015) .

7.4 Implications

Teams have become the default approach to accomplishing work in modern organizations (Gerard 1995) in which collaboration is increasingly distributed and digitally enabled (Carley and Ahuja 1999). Scholarly examination of the temporal nature of virtual collaboration dynamics (Gilson et al. 2015) has been lacking. This study has potential to contribute to what is known about the trajectories of virtual innovation teams and more generally with respect to virtual team performance. The design of this dissertation study was innovative to the extent that insights emerging from our results have clear potential to contribute to those generated by previous research on virtual team innovation. New theoretical insights often come from use of methods and data sources outside of the dominant methodological paradigm (McGrath et al. 1982).

7.4.1 Implications for Virtual Teams

As virtual collaborations are increasingly "ubiquitous and unavoidable for organizations" (Suh et al. 2011, p. 352), all teams are becoming more virtual. Well-recognized is the need to identify network structures of the sort that enable virtual teams to overcome challenges of coordination and knowledge integration. But those configurations lack clarity, as do accompanying interaction dynamics. Modern organizations need best practices for the design and management of teams that flourish not in spite of their virtualness, but rather because of it.

Our longitudinal study and network-based approach in a health care innovation context is well-suited to fill various gaps in what is known about virtual teams. A recent review paper on virtual teams indicates that current studies in the medical field are limited, as are studies of teams spanning organizational boundaries (Gilson et al. 2015). Exceptional longitudinal research may be found on virtual teams (Geister et al. 2006; Metiu 2006) but the majority of virtual team studies remain cross-sectional, despite known limitations (Golden and Fromen 2011). Gaining insight into virtual team dynamics will require incorporation of longitudinal designs into future research (Gilson et al. 2015). Another emerging approach to study virtual team collaboration is social network analysis, particularly with regards to knowledge exchange (e.g. Capece and Costa 2009). Finally, frontiers of virtual team research include adaptation to task demands and the nature of creativity (Gilson et al. 2015).

Thus our study design is situated to fill in some gaps in the theoretical understanding of virtual teams. Recent studies of virtual team effectiveness have examined action processes including coordination, communication, and knowledge integration, key challenges facing teams with dispersed and often diverse membership (Gilson et al. 2015; Kock and Lynn 2012). This diversity is a key element of the promise of virtual teams. But that diversity must be managed and harnessed to create conditions from which value emerges out of individual contributions. Virtual teams that can transcend challenges of coordination are positioned to reap cognitive and generative benefits.

We observed that higher centrality of team network structures was associated with enhanced team outcomes. It may be that the presence of central team members offers benefits for virtual teams that outweigh coordination costs. In Chapter 2 we discussed information elaboration, the sharing of team member information resources in ways that generate new knowledge and actionable solutions (Resick et al. 2014; Van Knippenberg et al. 2004). An individual situated at the center of the team communication network likely has insight with respect to expertise location (Faraj and Sproull 2000). While central individuals may impede the open, decentralized communication that we envisioned as important for virtual teams, the value of centrality in harnessing the diverse knowledge of dispersed team members may be essential for team effectiveness in some virtual collaborations.

Dynamism with respect to levels of team centrality may signal team convergence around a leader (high centrality), followed by dispersion of team members to carry out individual tasks or seek external sources of knowledge (low centrality). Such fluctuations in centrality may also be indicative of shared leadership behaviors (Carson et al. 2007; Pearce et al. 2004) and effective integration of knowledge resources from each team member (Kanawattanachai and Yoo 2007). A firm-level study of strategic partnerships explored the impact of rotating leadership activities from one organization to another to be associated with successful collaborative and combinatorial processes for innovation (Davis and Eisenhardt 2011). Managers who can coax leadership behaviors out of multiple team members are likely to be rewarded with effective teaming. Our results suggest that decentralized/democratic team structures, regular changes in structures, and comparable levels of initiative from each collaborator will be drivers of virtual innovation team performance.

7.4.2 Implications for Innovation Teams

Team-level innovation is a function of ongoing interpersonal discussion (King and Anderson 1990) and may be conceptualized as a set of collaborative, information-processing activities (Moenaert et al. 2000). Successful innovation teams develop modes of interacting that support the integration of knowledge and experience to create new value as a collective (Majchrzak et al. 2012). Few individuals excel at both idea generation and implementation (Gutnick et al. 2012; Miron et al. 2004), one explanation for the prevalence of teams as a strategy for innovation and new product development. Innovation teams need talent for generating new ideas as well as team members who excel at enacting those ideas and selling them to peers, lead testers, and eventually end-users (Miron-Spektor et al. 2011a). Thus development of communication strategies and recognition of network structures that capitalize on individual diversity are as important for innovation teams as we have shown them to be for virtual work groups.

Innovation work is often conceptualized as a series of phases in the lifespan of an innovative idea that vary with respect to the capabilities and cognitive processes required of innovators (Basadur and Gelade 2006; Boeddrich 2004; Tushman 1977; Veryzer 1998). When we considered radical innovation as a focal outcome, we observed different effects across innovation process phases than when performance was examined as the outcome. Contrary to what we expected, we observed the strongest positive association between participation equality and innovation during implementation phase, with a weak negative relationship during earlier phases. It runs counter to our theoretical development for the benefits of participation equality for innovation to materialize during the final phase. Perhaps the unexpected pattern that we observed across phases reflects the limitations of the phase model in understanding how innovation unfolds via interactions within teams.

Innovation process phases may also be less theoretically relevant to our study of within-team interactions (observing only known team members) as opposed to consideration of a team network as it is embedded in the broader networks of each of its members. As a team moves from abstract development and prototyping to instantiation of their idea and field testing, we would expect team network structures to change as a function of success in testing ideas in an increasingly broader range of contexts. This work would involve connecting with more practitioners and with others from the extended team network who could offer fresh insights or feedback. Thus our observation of within-team networks may not detect more prominent phase-driven changes occurring to the team network with respect to external connections. The use of innovation process phases as a moderating variable could prove to be much more potent using observations of extended team networks. Our study focused on internal communication amongst team members, but external communication and peripheral network ties are equally important considerations in understanding what drives successful innovation teams (Ancona and Caldwell 1992; Cohen and Levinthal 1990; Hoang and Rothaermel 2010; Hülsheger et al. 2009).

To be sure, recognition of the distinctive phase challenges that follow an idea through its lifespan from inception to implementation is necessary for innovation success, but it is not sufficient. Our results caution against overreliance on the stage/phase framework in designing and managing for innovation teams. It is reasonable to conclude that the optimal team structures and communication patterns for generative information flow differ from those that facilitate constructive conflict and negotiations amongst team members in defining and developing an idea. And if that is the case, the logistical and cognitive challenges that we have associated most strongly with one particular phase are likely to be occurring within each phase.

In a classic paper on organizational learning, March identifies two distinct yet complementary work modes: “the exploration of new possibilities and the exploitation of old certainties” (March 1991: 71). This framework resonates with the iterative nature of innovation processes that involve searching for new ideas (exploration) and refining those ideas that show promise based on testing and learning (exploitation). Several studies have used network analysis to observe how communication network structures differ when participants are in exploration mode versus exploitation mode (Lazer and Friedman 2007), or working in information space versus solution space (Shore et al. 2015). The takeaway here for managers is that innovation and new product development work modes could fluctuate regularly in addition to responding to broader evolutionary patterns for innovation teams reflected in phase models.

7.4.3 Methodological and Practical Implications

Our methodological decisions were motivated by the dearth of longitudinal research approaches to study technologically-enabled emergent change (Chomic 2009) and the need for more empirical evidence based on primary data sources in the knowledge network research stream (Phelps et al, 2010; Faraj et al. 2011). To capture the temporal nature of collaborative innovation (Poole and Van de Ven 2004), we incorporated time into our hypothesis testing and theorization. We also hypothesized explicitly about the moderating influence of distinctive innovation phases.

Social network analysis (SNA) has undoubtedly informed our study design and theorization; how in turn might our work contribute to this bourgeoning set of tools and methods? Observations in this dissertation study were based on digital traces of email correspondence. Modeling team communication networks over twenty-three months, we demonstrated the promise of dynamic digitally enabled SNA as an emerging paradigm for observation of (and intervention in) collaborative phenomena (Lazer et al. 2009; Watts 2007). The digital and longitudinal features of this research supplement dominant methods used in existing scholarly examination of virtual collaboration and innovation in teams (Scott 2012).

"Social networks lead a double life"; they are both the reality of interpersonal connections and the social constructs perceived by network actors (Mehra et al. 2014: 312). Most conventional network studies draw on self-reported data on the nature and intensity of relationships (Lazer et al. 2009). Survey- and census-based data collection of individual's ego-network information relies on memories and bounded perspectives, subject to recall and social desirability biases (Marsden 2005). Informant accuracy in generating social network data (Bernard et al. 1982) has been broadly studied and criticized in some cases. Idiosyncratic personality traits can impact accuracy of informant in perception of their social network, as does their position in the network (Casciaro 1998). The informant's formal status in their organization and the nature of relationships to be perceived affect perceptual accuracy (Marineau et al. 2013).

The use of social network models generated by digital traces is increasingly common and not without its own set of vulnerabilities (Crowston et al. 2010). The digital traces approach is valued for avoidance of common measurement biases in secondary network data collection and for the mapping of the method to actual network flows (Tortoriello et al. 2012; Wu et al. 2011). The set-up process for email collection was momentarily intrusive for our study participants; once established, passive longitudinal collection of email data allowed for observation of communication behaviors without multiple requests for data collection and reliance on retrospective accounts.

Practitioners are likely to find the methods used in this study to be more informative than any of the results. Digital traces of online interactions abound in modern organizations; these data are an untapped source of business intelligence (Riopelle 2012). Network-based feedback for teams promises to capitalize on visibility and other new learning opportunities afforded by information and communication technology (Grippa et al. 2012). But also important to consider is how what is made visible about work will change the ways that we work. Exploratory and empirical research is needed to test and compare network interventions in different contexts (Valente 2012). Practically, in health care systems and elsewhere, the results of this study could inform the design of multi-intervention innovation initiatives, value networks, and social change incubators, as well as improve their implementation (Fjeldstad et al. 2012).

7.5 Conclusions

The advent of the internet introduced exciting opportunities for collaboration across time and space. Network-based knowledge collaboration has emerged in new organizational forms across temporal and spatial boundaries in diverse industries and social contexts. Virtual teams are a basic unit of collaborative innovation work, yet structures and mechanisms that support exceptional innovation in virtual working groups are not well-defined. This dissertation contributes to enhanced understanding of processes and performance in virtual innovation teams and may guide future inquiries in this research domain.

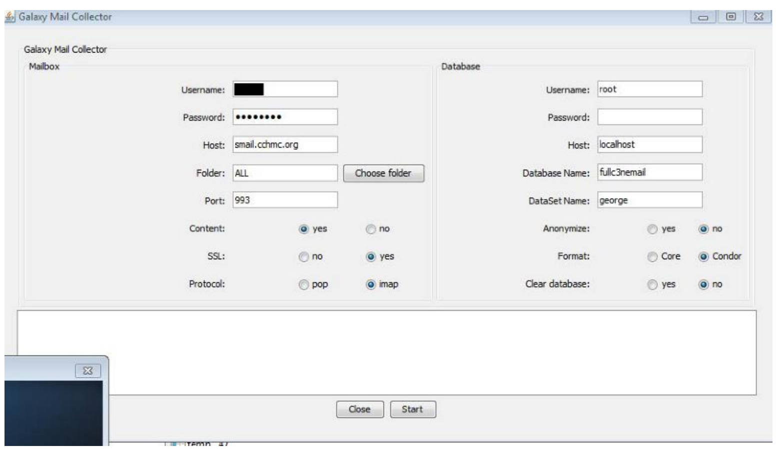
Appendix A: Email Data Collection Technical Logistics

This guide was developed by the fantastic research team supporting this study at Cincinnati Children's Hospital Medical Center.

<u>EMAIL COLLECTION METHODS (3)</u>

1. **GroupWise** (Original)

The original email platform at CCHMC was GroupWise, which had the IMAP enabled allowing participant's data to be directly imported from the mail client to Condor. In order to prevent CCHMC credentials from being shared, GroupWise allowed user's to temporarily change their email password so that it was different from their regular CCHMC credentials. Prior to each import, participants were asked to temporarily change their email password and provide it to the Research Coordinator, which would then be used along with their CCHMC user ID within Condor to import their email data. After import was complete, the participant would be notified and reminded to change their temporary password back to their original CCHMC credentials.



All email data was collected via direct import from GroupWise, so the data had to be manually cleaned by the Research Coordinator and study staff after collection. Once data was imported in to Condor, the files could be reviewed via Navicat. Sorting, filtering and cleaning of the data were managed by the Research Coordinator prior to analysis. Data cleaning could take up to 1 business day to perform, depending on the amount of data per individual participant.

Eight (8) participants were included in the original analysis, with partial download occurring July-November 2010 with a second full download/data collection occurring December 2010.

2. **Export + Convert** (Temporary Method): February 2012-April 2013* (Approx. 14 Months)

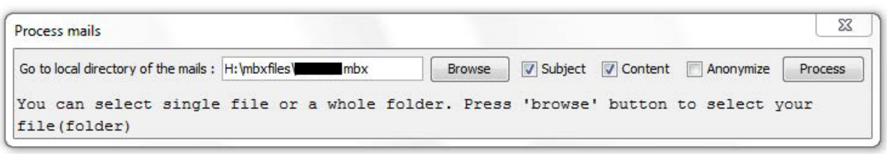
IS REQUIRED:

After the switch from GroupWise to Outlook at Cincinnati Children's Hospital Medical Center, new hurdles resulted in obtaining email data for collection and analysis with Condor. This method required email data to be exported from Outlook as .PST files, which then had to be converted to MBX file format for uploading in to Condor.

CCHMC presented a unique set of challenges for obtaining email data for collection and analysis with Condor. Due to a "security policy to prevent users from exporting email with Outlook's export feature", the data export from Outlook could not be completed by the Research Coordinator from their designated work laptop.

IS became a crucial part of the data collection process, and had to perform both the data export of .PST files and the file format conversion to MBX. After completing each individual participant's email data export and conversion, the confidential files were saved directly on the Research Coordinator's private network drive for access and uploading to Condor.
Requiring IS for exports provided an inconsistency in terms of data collection timing, and unpredictable turn-around for requests. It also required a massive, manual data cleaning effort by the Research Coordinator.
Data exports took place: August 2012 (partial), November 2012, January 2013, March 2013, April 2013 and July 2013.

1. Export .PST email data from Outlook
2. Convert to MBX file format
    a. Save on private network drive
3. Open Condor
    a. File>New >eMail Database>
4. Edit>New Dataset > [name dataset – i.e. The name of the person whose email is being uploaded]
    a. Note: Name must be MORE THAN 4 characters
    b. Browse>Select MBX file you want to upload>Check Subject AND Content>Click Process



    c. After completed, it will read "parse is done." Click the X to close out, and repeat step 5 until all email is uploaded

RESEARCH COORDINATOR:
During the initial data exports, the Research Coordinator worked with each participant on a list of names and topics that were to be flagged and removed from the study. Once data was imported in to Condor, great care was taken to review the files via Navicat. Sorting, filtering and cleaning of the data were managed by the Research Coordinator prior to analysis. Data cleaning

could take up to 1 business day to perform, depending on the amount of data per individual participant.

MAC USERS*:

Participants who worked from a Mac continued to have their email collected beyond April 2013 via the Export + Convert method, performed by IS. The collection was performed at varying intervals, while the Research Coordinator continued to work on solutions for collecting email data directly from the Mac user without involving IS. The "Mac Solution", described below within Email Collection Method #3, was confirmed with IS in December 2013.

3. **Outlook + IMAP** (Current): April 10 2013*- [DATE TBD]

For the Team Science Study, collection of C3N Project specific email from identified, voluntary project staff needed to occur in a systematic, simplified and regular manner. Both incoming and outgoing email needed to be collected, without exporting through IS support; which required an IMAP account solution that could directly plug in to Condor, as well as a mechanism to filter email without manual data cleaning. Five solutions were developed in January 2013, with a final solution being implemented in April 2013.

Data collection procedures for each participant (Apple Mac users' procedures vary, see "IMAP for Apple Mac Users" below):

1. The Research Coordinator (RC) sends an IRB approved information sheet to potential participants and have participant agree to have email collected (RC allows 7 days for participants to agree to participate before a reminder email is sent)
2. RC creates a tracking log that includes all participant information related to IMAP collection including: IMAP username, password, primary SMTP address, IMAP account status, notes, and dates of export. This is securely maintained by the research coordinator, and updated throughout the length of the study.
3. If agreement to participate is made, RC emails CCHMC IS to setup IMAP account for participant (this process can take about 4 weeks for IS to complete).
4. CCHMC IS creates IMAP account for participant and notifies RC with the IMAP username, password and host ID for each participant. This information is added to the tracking log by the research coordinator. Please note: IMAP accounts are established on an ongoing basis throughout the study, so this process did not just occur at the beginning; a relationship with IS to be maintained throughout the study.
    a. This unique login information is separate from the participant's existing CCHMC credentials, and is not shared with the participant; this allows the research study to avoid sharing passwords and ensures proper security.
5. IMAP Rules Setup – original process (5a) and enhanced process (5b)

a. Original Process: RC notifies participant and sends IMAP rules setup instructions for participant to set up rules within Outlook (setup is a 30-minute process for the participant). The RC allows participant 10 business days to complete IMAP rules setup; this may be extended based on participant needs. Please note: Outlook rules enable both sent and received to be copied to the IMAP account.
b. Enhanced Process: The project team noticed extended delays from the participants to complete the IMAP rules setup. The assumption was made that these delays may be caused due to the amount of time and effort involved in completing the IMAP rules setup. The project team also noticed that when the rules were independently setup by the participants, there were usually errors that resulted in emails not being copied to the IMAP inbox. As a result, the original process (see 5a, above) was enhanced in February 2014 to offer more assistance during setup and eliminate a major portion of the IMAP rules setup instructions that caused the delays and issues noted above. A total of 33 steps were removed after enhancing the IMAP rules setup process for participants (total time for IMAP rules setup after enhancing is 15 minutes; resulting in 15 minutes less than the original 30-minute process).
    i. Participant completes steps 1-8 in Team Science IMAP rules setup instructions
    ii. RC connects with the participant via Microsoft Lync and uses the screen share and remote access features to setup IMAP remotely. RC spends time explaining how the IMAP inbox will be collecting the participant's email; RC also explains how the participant can monitor for errors
    iii. RC exports rules from his PC and imports to participant's PC

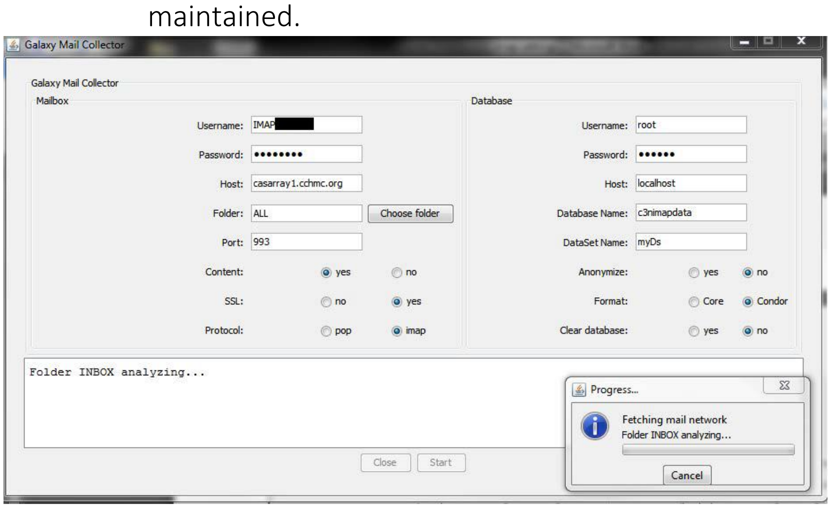
6. RC is notified by participants for any errors that may result in the IMAP rules abruptly turning off, resulting in emails not being copied to the IMAP inbox. Participants could usually identify errors either by noticing that his/her IMAP inbox is not collecting email or by an error message shown on the participant's Outlook window. The RC may also notice errors for participants' IMAP that during the email export using Condor as the export will complete at an unusually high-speed rate (e.g., an export that usually takes one hours completes in only 5 minutes). If errors are found the RC immediately responds to the participant to resolve the issue. In most cases issues were not ongoing and could be quickly resolved by the RC with minimal effort (within 1 business day); in a very select few cases the issues had to be escalated to IS due to the complexity of the issue (1-3-day process).
7. For activated participants, email data collection occurs on a bi-monthly basis.
    a. There is a strict institutional policy that requires all email to be archived/removed every 120 days. To eliminate the risk of losing any email data within IMAP accounts,

the RC performed the below mentioned process every two months starting in April 2013.

   b. *Data was exported: August 2013 (August 12*; August 22); November 2013; January 2014; March 2014 (April 1-8)*

8. 3-5 days prior to email export/data collection, the RC emails all participants and reminds them to check their IMAP inboxes for functionality and to ensure only C3N Project related emails are present – thus encouraging them to do a manual cleanup of their IMAP, in case the Outlook rules did not prevent all unrelated email to copy over.
   a. Participant communicates any issues to the RC and cleans IMAP inboxes for any non-C3N Project related emails
9. Data collection must occur within CCHMC's internal network, on a secure Wi-Fi connection (i.e. CCHMC credential certified). RC uses MacBook PRO (20 GB Ram), a separate machine obtained specifically for use in the study to run Condor. Each participant's IMAP inbox is individually imported through the Mail Collector, using the IMAP credentials provided by IS (each export can take between 30 minutes to 2.5 hours, depending on the amount of emails in the IMAP inbox. This is usually a 3-day process for the research coordinator).
   a. Total IMAP ever established were 29, and of those only 24 became active; currently there are 21 active IMAP accounts participating in the study (THIS NUMBER MAY CHANGE).

   b. One database is maintained throughout the study to host the IMAP data collection: TeamScienceIMAP. Within the database, each dataset is specific to each individual participant; noting at least their first name, if not also including last name/initial (all one word, character limit). The same database name, and same dataset names, must be used at each data collection point to ensure data is cleanly organized and maintained.



   c. RC updates tracking log each time a participant export is completed, noting the date of export.

10. RC notifies Team Science project team after all IMAP accounts have been imported via Condor. The updated, original database is

then stored/distributed via the secure, IRB-approved Xythos account to be analyzed by the team.

"Mac Solution" – IMAP for participants that are Apple Mac users:

IMAP inboxes were not supported on Apple Mac computers or the web Outlook client which limited our ability use the standard IMAP collection and export format that we had already setup for PCs (i.e., email forwarding followed by an export using Condor). We had two Mac users which included both co-principle investigators of the C3N Project. Because of the critical role the two Mac users held in the C3N Project, it became very crucial that we discover a method to collect email from the Mac users. We explored an array options with CCHMC IS to get around the Outlook IMAP email forwarding issues with Mac computers. Our first workaround required CCHMC IS staff to manual complete exports of Mac users' email that would then be converted to be imported into the study database. This method was not feasible long term as our staffing resources in IS were very limited. After 10 months (February 2013 to December 2013) of testing various methods for Mac, we established a method that would allow us to collect emails into an IMAP account from CCHMC Mac users.

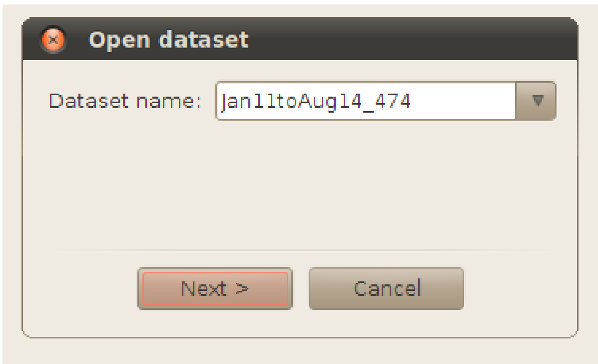
The established method is not very efficient, but did allow for the study to collect valuable email from two critical C3N Project staff. The method we employed required a Team Science RC to have the Mac user to personally log on to the coordinator's PC. After login, the RC opened Microsoft Outlook, which downloads/syncs all email currently included in the Mac user's account over to the local Outlook client (the Outlook on coordinator's PC). This process of downloading email into the local Outlook client can take 1 hour or more, depending on the number of emails each user received.

Once all of the emails were downloaded to the local Outlook client, the research coordinator, using Outlook on his PC, copied (CTRL-C) all emails from the user's inbox (including any relevant cabinets/subfolders), any deleted mail, and any mail in the sent box over to the IMAP account/inbox (CTRL-V). This process can take up to 3 hours to complete per user. The coordinator needed to monitor the copying activity frequently as errors could occur which would require starting the coping process from where the error was determined (i.e., see which email was last copied over to IMAP and continue from there) (This entire process would take an average of 3.5 hours per user – 7 hours for both users).

There is a strict institutional policy that requires all email to be archived/removed every 120 days. To eliminate the risk of losing any email, the coordinator performed the above mentioned process every two months starting in December 2013.

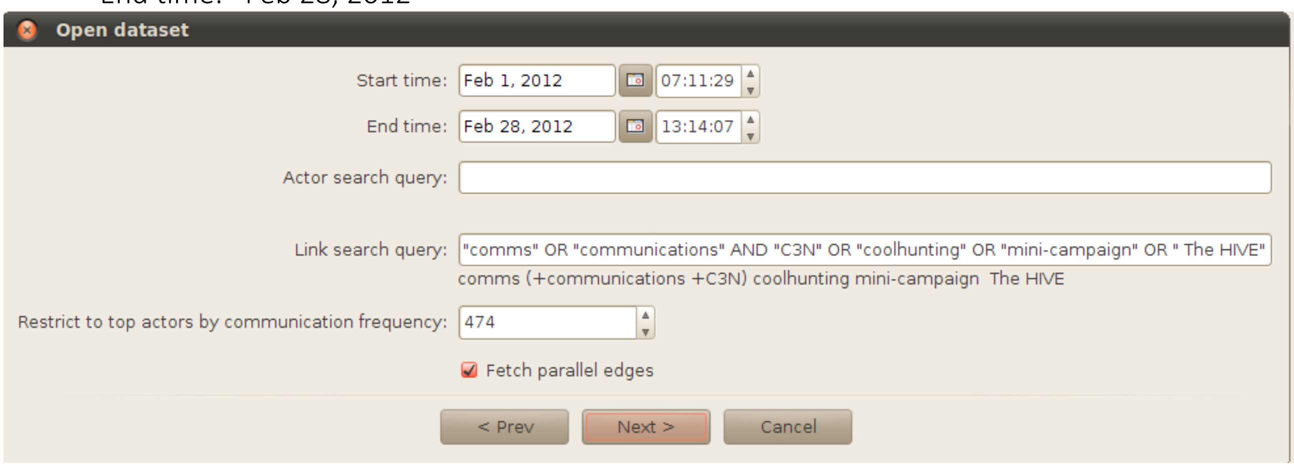
Appendix B: Condor software platform settings used to generate network observations

1. Open dataset:

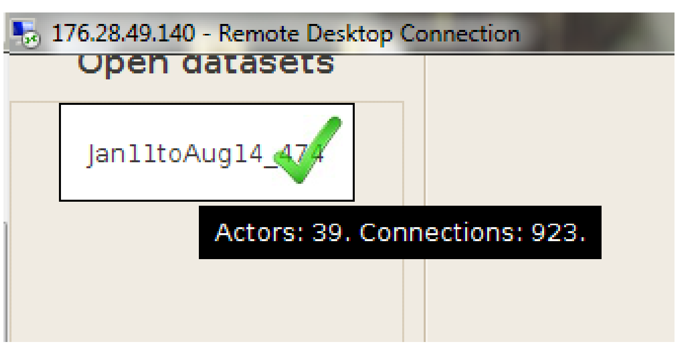


e.g. Start time: Feb 1, 2012 Link search query: KEYWORDS FOR TEAM

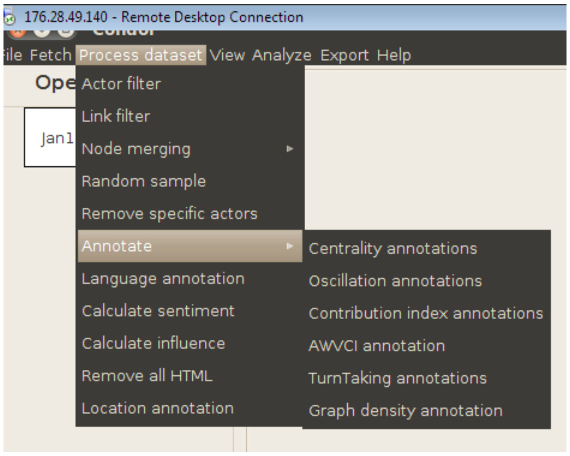
End time: Feb 28, 2012



2. Hover on dataset icon at left; record by hand # actors and # connections (or take screenshot)

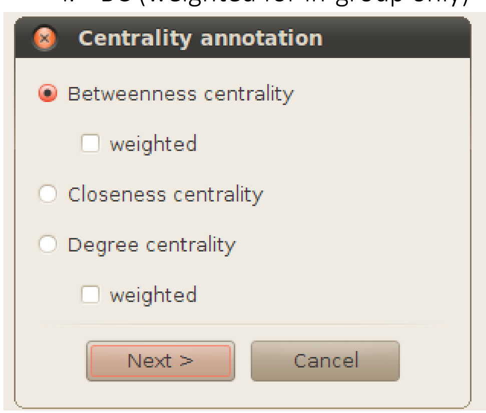


3. Process Dataset > Annotate

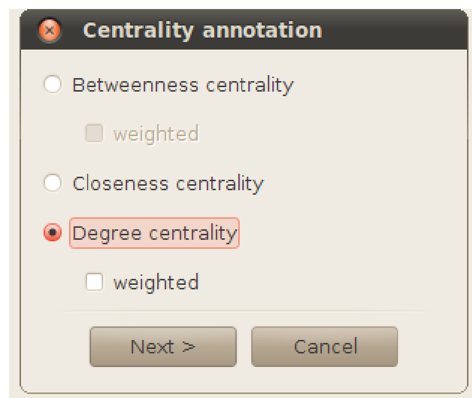


a. Centrality

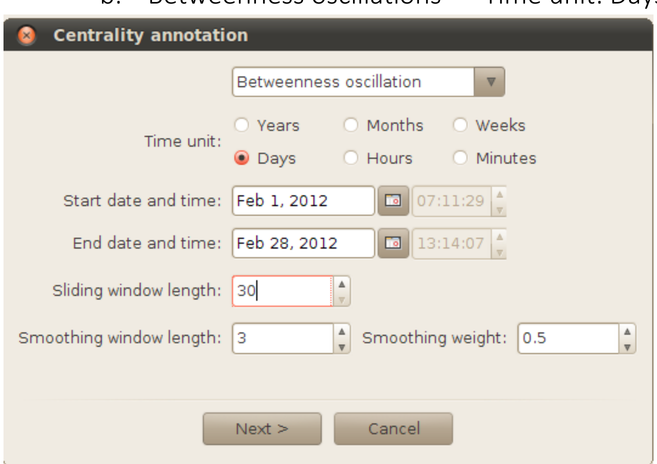
i. BC (weighted for in-group only)



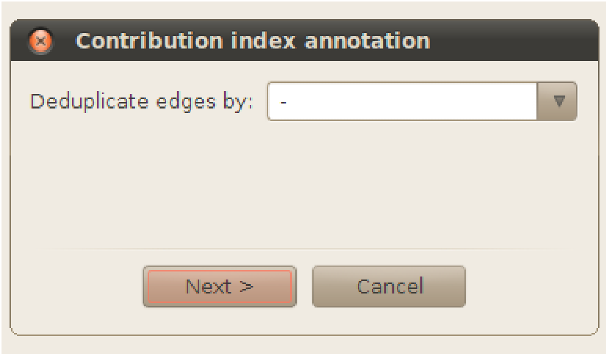
ii. DC (weighted for in-group only)



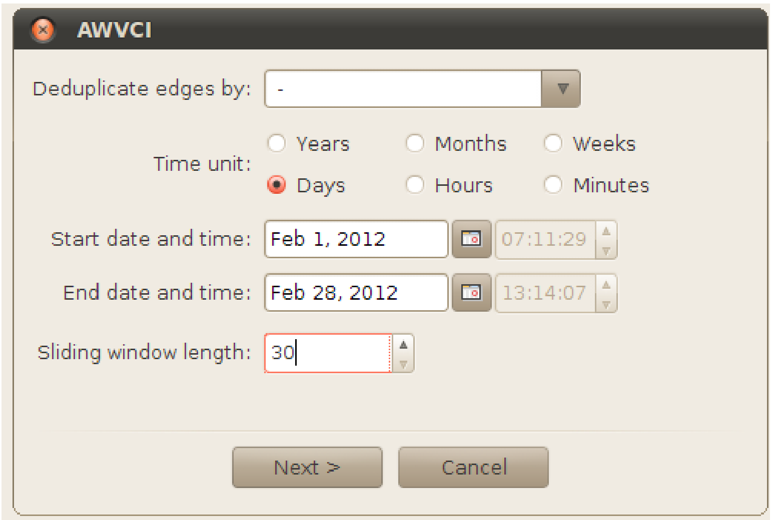
b. Betweenness oscillations Time unit: Days Sliding window length: 30, 7, 1



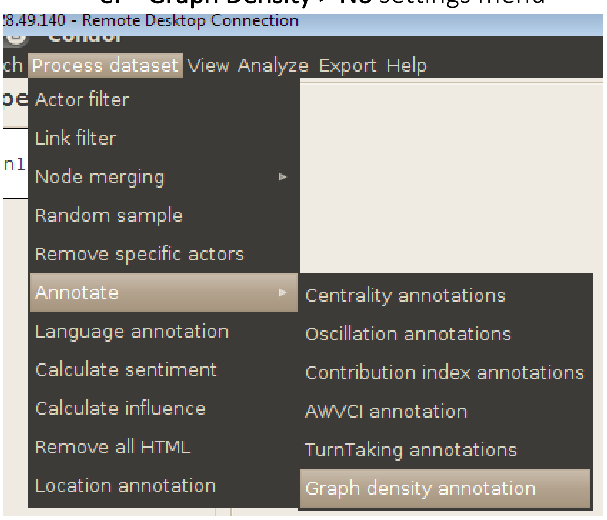
c. Contribution Index



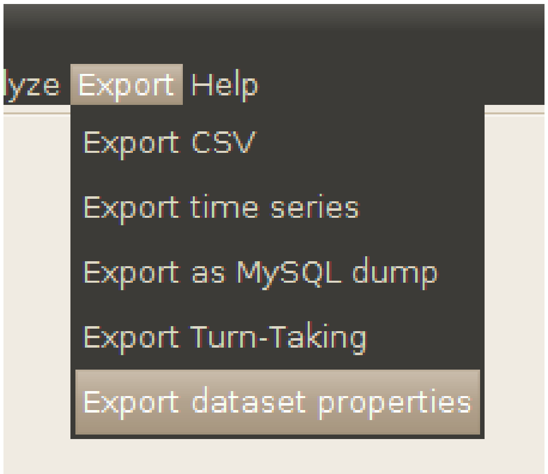
d. AWVCI Time unit: Days Sliding window length: 30, 7, 1



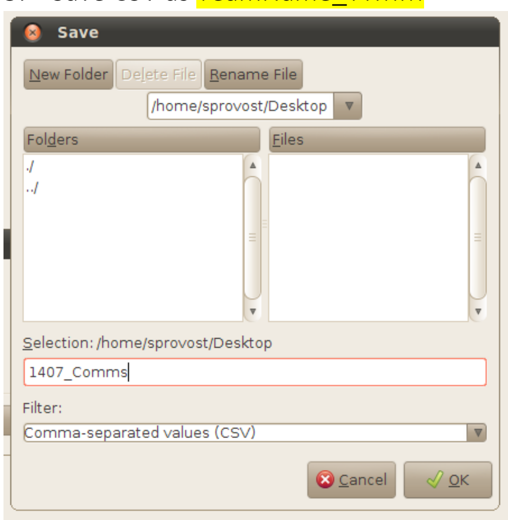
e. Graph Density > No settings menu



4. Export > **Export dataset properties**



5. Save CSV as TeamName_YYMM



Appendix C: Validation of Network-Based Measures across Teams

The use of email messages and other digital trace data remains on the methodological cutting edge of network-based organizational research. But a digital approach is increasingly recognized as a valid and often preferred alternative to the sociometric data used for conventionally for social network analysis (Crowston et al. 2010; Johnson et al. 2012; Kazienko et al. 2009; Van Alstyne and Zhang 2003). Numerous previous studies used email data collection processes that served to inform our approach as well as the same network-based software platform (Condor) that supported analysis in this study (Gloor et al. 2014; Gloor et al. 2003; Gloor et al. 2008; Grippa et al. 2011; Grippa et al. 2012; Grippa et al. 2006; Kidane and Gloor 2007; Merten and Gloor 2010; Palazzolo et al. 2011; Zhang et al. 2013).

After primary data collection and subsequent analyses to generate team-specific network models as described in Chapter 4, we characterized those network models with statistical properties that would serve as secondary data used to test our hypotheses. Before attempting to formally test our hypotheses, we conducted extensive descriptive and graphical analyses to evaluate the extent to which our data represented the underlying interaction dynamics that we intended to observe.

We created profiles for each team that included network graphs, contribution index plots, time series charts, and team artifacts. This contextual information helped with interpretation of results and supported the face validity of our digital observations. Network graphs also served as a helpful check on quantitative measures generated by the network models. For example, we identified high and low observations of team centrality and visually checked the network graph associated with the team and time that generated that observation. Reassuringly, this process allowed us to confirm that those email networks resembled a star structure or a highly connected hive, as we would expect to see for high and low levels (respectively) of the group betweenness centrality measure.

For each variable, we also generated graphics that included histograms, box plots, scatterplots, time series charts, and Shewhart charts. With these graphics, we wanted to verify that email-based network measures effectively detected variation across teams and over time. These charts were also used to identify special cause variation that would suggest that the measures were not uniformly representing networks across teams. We also used these charts to identify outlying observations warranting visual inspection of network graphs. We sought to distinguish observations that reflected real underlying differences in communication patterns from observations resulting from an anomaly of the email data collection process (for example, an email blast unrelated to an innovation project but containing a team-specific keyword). In the latter case, some messages were manually removed from our dataset.

De-identified team network graphs and contribution index plots as well as graphical summaries for each network-based measure are available on request.

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